Eastern Research Group, Inc.

Estimating Benefits of Improvement Strategies (including RSD) for the California I/M Program: An Inspection and Emissions Forecasting System

REPORT
Version 7 (final)

Prepared for:

California Air Resources Board
and
California Bureau of Automotive Repair

Prepared by:
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March 1, 2008

ECN: 0187.00.001.003

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March 1, 2008

DISCLAIMER

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Glossary

AFD – ASM Following Decision. The first next-cycle initial-test in an I/M program that follows the decision point.

AIR – Air Injection Reactor. A common emission control system on gasoline engines where air is injected into the hot exhaust gas to help further oxidize hydrocarbons and CO.

ASM Mode – Either the ASM 2525 test mode or the ASM 5015 test mode.

ASM Mode/Pollutant – One of the six combinations of ASM modes (2525 and 5015) and ASM pollutants (HC, CO, NX).

ASM Pollutant – Either HC, CO, or NX.

Average-Performing Station – A hypothetical category of I/M inspection stations that have the average ASM inspection performance of all stations in the California I/M system (including Test-Only, Test-and-Repair, Gold-Shield, Referee, etc. stations), on all vehicles inspected, and for the study's historical VID data period for ASM inspections (July 1998 through April 2005) taken as a whole.

BAR-90 – A system of analytical instrumentation and database software that was used before about June 1998 to perform and record California I/M program inspections. Almost all emission tests for BAR-90 were two-speed idle tests.

BAR-97 – A system of analytical instrumentation and database software that has been used since about June 1998 to perform and record California I/M program inspections. Both two-speed idle and ASM emission tests are handled by the BAR-97 system.

Brown ΔCprob – ΔCprobs calculated from Cprobs that begin later than the first month after the previous-cycle inspection.

Call-In ASM – A mid-cycle ASM test performed to determine if a vehicle needs to be repaired before its next regular I/M test.

Calling-In No-Sticker – An I/M program improvement strategy in which high-risk vehicles are requested mid-cycle to get an ASM test. Vehicles are not given a new 24-month certification for meeting call-in ASM requirements. In this instance, vehicles must follow the reinspection requirements of their existing certification even though they have participated in the call-in process.

Calling-In Sticker – An I/M program improvement strategy in which high-risk vehicles are requested mid-cycle to get an ASM test. In this instance, vehicles that meet call-in requirements are issued a new 24-month certification at the time of the call-in ASM. The vehicles are, therefore, on a new reinspection schedule and would be expected to receive their next-cycle inspection in about 24 months after the call-in ASM.

CN – Calling-In No-Sticker

CS – Calling-In Sticker

Conditional Fprob – A failure probability that is contingent upon another event. In this study, an example of a conditional Fprob model is one that calculates the failure probability of ASM 5015 CO given that the ASM 2525 CO was a pass.

Cprob – The cumulative I/M completion probabilities. The probability that a vehicle will receive its next-cycle certification within a given number of months after its previous-cycle certification.

ΔCprob – The difference between the subsequent-month Cprobs. The probability that a vehicle will receive its next-cycle certification in a particular month after its previous-cycle certification.

Decision Point – The date when a decision is made to intervene in the Normal I/M Process or not. If RSD is supplementing the I/M program, for Calling-In and Scrapping the Decision Point may be triggered by an RSD measurement event, and for Exempting and Directing the Decision Point may be triggered by the biennial anniversary of the most recent certification. If RSD is not supplementing the I/M program, the Decision Point for Calling-In and Scrapping may be triggered by some criterion other than an RSD measurement. For example, it could be triggered randomly in time.

DI – Directing

Directing – An I/M program improvement strategy in which vehicles that are expected to soon appear for their biennial inspection are sent to high-performing stations instead of allowing the vehicle owner to choose the inspection station. In general, high-risk vehicles are directed.

EGR – Exhaust Gas Recirculation. An emission control system in which exhaust gas, which is inert, is recirculated back to the intake manifold to reduce combustion temperatures and, thereby, reduce nitrogen oxides emissions.

Engine – An engine descriptor used in this study to classify engines. The descriptor is made up of the engine displacement, cylinder configuration, and aspiration (natural, turbo-charged, super-charged).

EX – Exempting

Exempting – An I/M program improvement strategy in which vehicles that are expected to soon appear for their biennial inspection are allowed to skip the inspection and receive a standard 24-month certification. In general, low-risk vehicles are exempted.

Fast-Pass – A method of emission testing in which the test is terminated prematurely when instantaneous emissions values go below fast-pass emissions thresholds. In the California I/M program, fast-pass emission thresholds are equivalent to the ASM mode/pollutant cutpoint values.

FMD – Failed Miles Driven. An acronym to describe miles driven in an ASM-failed status over the 24 months following a decision point. The value is calculated by summing the monthly estimate of overall ASM failure probability times the number of miles driven in the month. It is a probabilistic value because the ASM failure probability is an estimate of the fraction of vehicles with the same vehicle description, VID history, and/or RSD measurements that would fail an ASM test.

ΔFMD – Change in failed miles driven over the 24 months following the decision point. ΔFMD is a measure of the change in failed miles driven caused by a selected intervention. A negative ΔFMD indicates that the intervention caused the failed miles driven to drop in comparison with the Normal I/M Process.

Fprob – The probability that a vehicle will fail a test. Fprob is also equivalent to the fraction of vehicles that would fail the test for those vehicles in the same circumstance. All Fprobs in this study are fractions.

ΔFTP/$ – The change in FTP mass emissions over the 24 months after a Scrapping decision in comparison with the Normal I/M Process divided by the market value of the vehicle.

High-Performing Station – A hypothetical category of California I/M inspection stations that would perform more-accurate I/M inspections and therefore would be able to provide greater emissions reductions than average-performing stations. In the analysis we did not attempt to determine which stations or which types of stations (Test Only, Test-and-Repair, Gold Shield, etc.) were average-performing or high-performing. Instead, based on station-performance information from BAR, subsequent reports will assume that the hypothetical high-performing stations have fail rates that are somewhat higher and after-repair emissions levels that are somewhat lower than those of average-performing stations.

Intervention – The act of taking special action that is beyond the Normal I/M Process. Examples of intervention include sending letters to I/M program participants for Directing, Exempting, Calling-In, or Scrapping.

Logistic Regression – A standard statistical regression technique in which the variable being modeled is bi-valued or ordinal. In this study, all of the variables being modeled using logistic regression are bi-valued with values of either pass or fail. See Appendix H for a review of logistic regression.

Logit – The natural log of the odds. The logit of an ASM Fprob equals ln(Fprob/(1-Fprob)).

Make_CarTrk – A vehicle descriptor used in this study to categorize vehicles. The descriptor is made up of vehicle make and vehicle type (car, truck).

Metering_ECS – A technology descriptor used in this study to classify emission control technology. The category is described by fuel metering (carbureted, fuel-injected), air injection reactor (yes, no), catalyst type (none, oxy-catalyst, three-way-catalyst), and exhaust gas recirculation (yes, no).

NIM – Normal I/M Process

Normal I/M Process – The process by which vehicles that participate in the California I/M program voluntarily get their vehicles inspected at I/M program stations in accordance with the rules for 24-month certifications. The Normal I/M Process includes biennial inspections and change of ownership inspections. The Normal I/M Process does not include, for discussion purposes in this study, Directing, Exempting, Calling-In, or Scrapping.

NX – One or more of the oxides of nitrogen. Although NO and NOx are measured differently and are different chemically, we make no distinction here.

Overall ASM Fprob – The probability that a vehicle that receives an ASM test will fail at least one of the ASM mode/pollutants.

Pink ΔCprob – A ΔCprob calculated from Cprobs that begin in the month after the previous-cycle inspection.

Pprob – The passing probability. Pprob equals 1-Fprob. All Pprobs in this study are fractions.

RSD – Remote Sensing Device. An instrument that measures the instantaneous tailpipe emissions concentrations of HC, CO, and NX of on-road vehicles by shining a light beam across the road so that it intercepts the plume from the vehicle's tailpipe.

Scrappage ASM – A mid-cycle ASM test performed to determine if the State should purchase the vehicle to retire it.

Scrapping – An I/M program improvement strategy in which high-risk vehicles are purchased from their owners by the State and destroyed. High-priority Scrapping candidates are those that produce a large mass of emissions and have a low market value.

SP – Scrapping

Time-dependent Fprob – Failure probabilities calculated by modeling the I/M program inspection test pass/fail results stored in the VID. The models contain some sort of time dependent functionality, such as for vehicle aging and/or time elapsed since the previous-cycle I/M inspection so that Fprobs can be calculated as a function of time.

Traditional Fprob – A method of estimating the generic tendency to fail I/M program emissions tests based on counting the number of passes and fails for each combination of model year and vehicle description in an I/M program historical VID.

Unconditional Fprob – A failure probability that is not contingent on any event.

Vehicle Description – In this study, a combination of Metering_ECS, Make_CarTrk, and Engine for a vehicle.

VID – An I/M program's vehicle information database, which contains a specified list of variables that characterize all past inspections of vehicles participating in the I/M program.

VID History – The entire list of records from the VID for an individual vehicle that describes all of the interactions between the vehicle and the I/M program throughout the period during which the vehicle was participating in the I/M program.

VSP – Vehicle specific power. A measure of the instantaneous power required per unit of vehicle mass required to move the vehicle at a given instant. The units of VSP in this study are kilowatts/megagram (kW/Mg).

Executive Summary

This report, which is known as the modeling report, is the first in a series of three reports that estimates the incremental benefits of adding remote sensing device (RSD) measurement capabilities to the existing California I/M Program. RSD is a technology that measures the tailpipe emissions concentrations of vehicles as they pass the RSD instruments on the side of the roadway.

The analysis in this report focuses on estimating RSD's ability to incrementally improve the performance of special strategies[1] that could supplement the existing California I/M program. The incremental benefits of adding RSD measurements to the special strategies are calculated as the difference in benefits when vehicles are selected for special strategies using vehicle rankings based on RSD measurements plus VID information[2] versus using vehicle rankings based on VID information alone. The benefits in this report are calculated for the hypothetical situation where all vehicles have VID information and RSD measurements available. Then, the implementation report, which is the second report in the series, will use estimated costs of RSD implementation and the estimated benefits from this report to evaluate different implementation strategies for a more realistic situation where RSD measurements are available on only a portion of the vehicles in the I/M fleet[3].

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[1] **Calling-In** likely high emitters for an off-cycle I/M inspection, **Directing** likely high emitters to high-performing I/M stations for their upcoming I/M inspection, **Exempting** likely low emitters from their upcoming I/M inspection, and calling-in low-value, likley high emitters that would be offered to participate in **Scrapping** if they failed an off-cycle I/M inspection.

[2] VID information for individual vehicles is derived from the historical records of I/M program inspections recorded in the VID (vehicle inspection database) for an individual vehicle.

[3] As will be shown in the implementation report, a large RSD data collection program in the five largest AQMDs would be able to provide usable (i.e., emissions-representative) RSD measurements on only about 40% of the vehicles in the statewide I/M fleet. In contrast, VID information is available on almost all vehicles in the statewide I/M fleet.

The results of the analysis presented in this report can be summarized by answering two questions. When VID information and RSD measurements are both available:

1) What is the incremental benefit of adding RSD information to VID information?

   VID+RSD, in comparison with VID-alone, identifies vehicles with slightly higher incremental mass emissions during the 24 months between IM inspections and identifies vehicles with moderately higher fail rates at the instant of the ASM confirmation test.

2) Which produces higher incremental benefits to the I/M program – VID-alone or RSD-alone?

   VID-alone, in comparison with RSD-alone, identifies vehicles with moderately higher incremental mass emissions during the 24 months between I/M inspections, even though RSD-alone identifies vehicles with moderately higher fail rates at the instant of the ASM confirmation test than VID-alone does.

Consequently, since the purpose of the IM program is to reduce mass emissions to the airshed, vehicle ranking by VID-alone is more beneficial than RSD-alone. VID information and RSD measurements working together are substantially more beneficial than RSD working alone and slightly more beneficial than VID working alone. The subsequent implementation report will evaluate whether the slight performance improvement produced by adding RSD measurements to VID information is worth the cost of making RSD measurements.

The executive summary begins with a discussion of the goals and strategies of the California I/M program to demonstrate where the potential use of remote sensing could supplement existing I/M activities. Next, since the goal of this analysis is to estimate benefits, benefits are defined. For this analysis we have supplemented traditional measures of benefits with new measures that we believe more closely reflect the goals of the California I/M program. Once we have defined benefits, we describe the methods that are used to forecast the benefits of different targeting strategies for individual vehicles. The detailed description of the development of the techniques used to make these forecasts forms the bulk of this report. The executive summary presents a specific example for one individual vehicle to demonstrate the results of benefit forecasting. Vehicles are prioritized based on the forecasted benefits to be achieved by different targeting strategies for each individual vehicle.

The results of this analysis report are a large set of performance curves that will be used by the subsequent implementation strategy report where both the costs and benefits of the various strategies will be discussed. Those performance measures are provided in the body of this report, and a summary of those results is provided at the end of the executive summary. In general, supplementing vehicle and VID history information with RSD information produced small improvements. Therefore, we know that the RSD information added some value to the strategies that do not require on-road data collection. The rest of the Executive Summary summarizes our approach to calculating the benefits of adding RSD to the I/M program.

The Intervention-Enhanced I/M Program

We need to describe the California I/M program so that we can see where on-road measurement of RSD emissions might fit and so that we define benefits in a manner that is consistent with California's goals. The **Purpose** of the California I/M program is to:

- Minimize fleet emissions to the airshed.

As a means to address this purpose, the California I/M program has chosen a simple **Fundamental Goal** and put activities in place to meet the goal:

- All vehicles must pass a biennial I/M station emissions test.

The I/M program goal acknowledges the influence of emission control technology on emissions through the use of technology-specific cutpoints; however, to make this goal simple, the I/M program goal deliberately ignores several factors that are important to vehicle emissions and to the above-stated purpose of the I/M program. These factors include the level of vehicle usage, emissions degradation after the biennial inspection, the mass of on-road emissions accumulated between biennial inspections, and vehicle aging.

California has long recognized that implementing only the fundamental goal of the I/M program is not sufficient to satisfactorily address the purpose of the I/M program. Additional activities are needed. In this report, we call these intervention activities – because they work in parallel with the fundamental goal activities and sometimes intervene in the progress of an individual vehicle through the I/M program. Examples of intervention activities include model year exemptions, cost waivers, directing vehicles to high-performing stations using gross polluter or high emitter profile criteria, roadside ASM testing, and roadside ASM testing of vehicles selected by RSD (proposed).

Intervention activities have a special goal that is entirely different from the fundamental goal:

- **Special Goal** – Efficiently target a subset of the I/M fleet to improve I/M program effectiveness and/or cost-effectiveness.

All of the above-mentioned intervention activity examples look only at an ASM failure at one point in time. If the cost of the interventions is inexpensive enough, this approach can make sense. However, if intervention is expensive, then using better vehicle targeting methods may be beneficial for intervention activities. Note that improved targeting is the goal; as far as inspections are concerned, the fundamental goal is still that vehicles must pass a biennial I/M station ASM test. For the question in this study – Should RSD be added to the I/M program? – the cost of performing RSDs across the state is high. Accordingly, to attempt to most accurately estimate the cost-effectiveness of implementation, we are obligated to try to target vehicles as efficiently as we can.

Because intervention activities go after a subset of the fleet, vehicles can be targeted to take into account anything for intervention activities. We believe that the objective of the I/M program is to minimize the number of miles that vehicles drive on the road in an ASM-failed status so that the mass emissions released to the airshed are minimized. Up to this point in the development of I/M programs, the focus of intervention activities (including RSD) has mainly been on simply finding the vehicles that fail an ASM concentration test rather than focusing on the vehicles that emit a large mass of emissions integrated over the biennial cycle.

The reason that the goals of minimizing failed miles driven and mass emissions emitted between inspections have not been pursued has been the lack of the technical ability to forecast these quantities. In this analysis study, we have made technical breakthroughs that make it possible to forecast (or backcast) the failed miles driven and FTP mass emissions of individual vehicles. This makes possible improved vehicle targeting for more effective intervention activities. It is important to understand that these improvements can be implemented whether or not RSD is added to the I/M program. The forecasting takes into account vehicle description, I/M program inspection history, level of vehicle usage, vehicle aging, emissions degradation after repair, and length of time until the next regular I/M inspection. If RSD information is available, it can be added to those quantities to further improve failed miles driven and FTP emissions forecasts.

The main question in this analysis is how much higher the benefits would be for Directing, Exempting, Calling-In, and Scrapping if RSD information is used in addition to other information versus if RSD information is not used with the other information. Before we are able to make the calculations, we need to define benefits.

Definition of Benefits

Many studies have been performed where the benefit to the I/M program has been measured by the change in measured ASM emissions concentration at the regular I/M inspection test. The change would normally be produced by a repair to a vehicle. The one perceived advantage of this measure is that it is easy to verify since emissions concentrations are in the VID. However, this advantage goes away since almost all passing ASM tests are fast-pass tests. Fast-pass ASM emissions concentrations are known to be higher, on the average, than full-duration passing ASM emissions concentrations. This results in an overall under-estimate of the benefit of the I/M program.

There are important disadvantages to this definition of benefit. First, the benefit is measured at one point in time, not over the 24 months that the vehicle is driving on the road. This means that the benefits by this definition overstate the true benefits of the I/M program since emissions degradation following repairs is known to occur. Second, the change in ASM emissions concentrations is not a measure of mass emissions, which are more relevant to the purpose of I/M program and to the emission inventory. Third, the change in measured ASM concentrations at the I/M test does not take into account the level of vehicle usage. Vehicles that are driven more miles produce larger amounts of emissions than vehicles that are driven very little. Finally, this definition of benefit does not take into account the time that remains until the next regular I/M test. The true benefit will be larger for a vehicle that has a long time until its next I/M test compared to one that has a short time to its next regular I/M test even though the change in measured ASM emissions at an intervention ASM test is the same. Overall, the best that can be said about using the change in measured ASM emissions at the regular I/M test is that, hopefully, it is correlated with the true benefits that accumulate over the 24 months between regular I/M inspections.

For this study, we will use two different quantities to define benefits. The first is the change in FTP HC, CO, and NX mass emissions (ΔFTP) produced by interrupting the Normal I/M Process with an intervention activity. The change in FTP mass emissions is summed over the 24 months[4] after the decision to make or not make the intervention. This quantity is directly applicable to the purpose of the I/M program, that is, to reduce mass emissions of the fleet. The second, and new measure of benefits, is the change in failed miles driven (ΔFMD) by a vehicle in the Normal I/M Process and the same vehicle after an intervention activity over the 24 months

[4] We chose to calculate benefits over the 24 months after an intervention since California uses a biennial inspection cycle. Using a shorter duration would potentially not capture most of the I/M benefits, and using a longer duration would be difficult because forecasts would need to be made beyond more than two future I/M inspections.

after the intervention decision. Failed miles driven requires a little more explanation since it is less familiar. The monthly FMD has contributions from the level of vehicle usage and the probability that the vehicle is in an ASM-failed status. For example, if the vehicle drives 1,000 miles per month and has an overall ASM failure probability of 5%, then the monthly FMD would be 50 miles per month (= 1000 * 0.05). The sum of the monthly FMDs for the 24 months after an intervention decision is the total FMD.

The result of these new benefit definitions is that many of the inadequacies of looking at the change in measured ASM emissions concentrations at the regular I/M test are overcome. Fast-pass ASM tests are not an issue and are not a problem. Both ΔFMD and ΔFTP benefits are a summation over the 24 months after an intervention decision and are not just one value at the one split second in time when the vehicle was repaired. These measures of benefits take into account the level of vehicle usage and emissions degradation after repairs. The ΔFTP benefits are on a mass FTP basis. The advantage of these two benefit measures are that the ΔFTP mass emissions are directly relevant to the airshed inventory and that the ΔFMD is directly consistent with the fundamental goal of the I/M program, that is, that all vehicles pass an ASM test – whenever it might be given.

Intervention Activities Evaluated in This Report

The analysis in this document specifically addresses the first four questions from Task 1 of the work assignment. These questions define, for this study, the intervention activities in which RSD was envisioned as a supplemental component of the I/M program. The study was required to investigate and answer these specific questions even though RSD could potentially be used in other ways. Accordingly, this study does not investigate the use of RSD in any way other than the ways referred to by the study questions. *The primary objective of this study is to assess the effectiveness of remote sensing technology as a supplemental tool to enhance California's inspection and maintenance program. Specifically, the pilot study shall determine:*

a. *Whether remote sensing technology can be used to improve the state's high emitter profile (HEP), used to direct vehicles to high-performing stations.*

In this study this intervention activity is called Directing (DI). Directing occurs for vehicles that are expected to soon receive their biennial inspection. For Directing, the vehicles that represent the greatest risk to the state would be required to be inspected at high-performing stations in the I/M program. Directing is already being performed in the I/M program as an intervention activity and is based on gross polluter assignments or the current HEP. The notion of Directing is based on the premise that high-performing stations are less prone to inaccuracies than are average-performing stations.

b. *Whether remote sensing technology can be an effective tool to "clean screen" vehicles and exempt them from the next scheduled smog check inspection thus reducing program costs.*

We have performed benefits calculations for this intervention activity, which we call Exempting (EX). Exempting would normally occur shortly before vehicles are expected to appear for their biennial inspection. Vehicles that are expected to be a low risk to the I/M program would be ranked higher on an exempting list. Vehicles that are exempted would be given a certification without coming in for a regular I/M test. Exempted vehicles would be expected to appear two years later for their next biennial inspection in accordance with their new certification unless they were exempted again. Exempting is expected to always increase emissions and failed miles driven. The goal of the vehicle prioritization is to preferentially exempt vehicles that would have the smallest increases, which would therefore represent the smallest risk to the airshed.

c. *Whether remote sensing technology can be an effective tool to identify high-emitting vehicles between regular inspection cycles and to document the emission reduction benefits of such a program.*

In the analysis in this report, we call this intervention activity Calling-In. In this study, we consider Calling-In at any time in the I/M program cycle. For the analyses, we performed benefit calculations for two different Calling-In options. The first is called Calling-In No-Sticker (CN) in which vehicles that are called-in mid-cycle would be given an I/M station ASM test and if they failed the test the vehicle would be required to be repaired and to pass a follow-up ASM test. However, for this effort the vehicle would not be given an emissions certification but would be required to continue on its existing regular I/M program schedule. The other policy option is called Calling-In Sticker (CS). In this case, the vehicle would also be called in for an intervention test performed at a regular I/M station and would be required to be repaired and to pass a follow-up ASM test. However, the vehicle would then be issued a new biennial certification. This would put the vehicle on a new regular I/M schedule.

d. *Whether remote sensing technology can be an effective tool to identify vehicles that would be, based on the vehicle emission levels (and overall condition), candidates for early retirement (scrappage).*

In this document we call this intervention activity Scrapping (SP). In this analysis, we consider Scrapping for vehicles at any point in their I/M program cycle. For these calculations, scrappage candidate vehicles would be called-in for a scrappage ASM test that would be performed at a regular I/M station. If the vehicle failed the test, the state would offer to purchase the vehicle from the owner for scrapping. Scrappage candidates would be selected from the fleet based on their estimated decrease in FTP emissions over 24 months per dollar of vehicle value. By using this ranking variable, the state will come close to maximizing the total mass of emissions that are reduced through the purchase and scrapping of the candidate vehicles.

Forecasting Failed Miles Driven and FTP Mass Emissions

To be able to rank individual vehicles for targeting for a specific intervention activity, we need to be able to rank the vehicles by the estimated benefit of performing the intervention on that individual vehicle. The estimated benefit is the difference between two forecasted "paths" for the vehicle: the path if the vehicle continues uninterrupted in the Normal I/M Process and the intervention path. In this study we have chosen the duration of the paths to be the 24 months after the decision to intervene or not. The vehicles where the difference between the two paths is large will be high on the vehicle targeting list for intervention.

Failed miles driven and FTP mass emissions will be forecast for the 24 months after the decision point for each vehicle. These quantities will serve as the basis for determining the potential benefits of intervening. The benefits of intervention will be used both for ranking vehicles for targeting and for evaluation of the benefits of different vehicle rankings.

The overall ASM failure probability for a given vehicle is not constant. It is a function of time because of vehicle aging and emissions degradation following repairs. Accordingly, we built two primary models[5] to calculate overall ASM failure probability at any point in time to be able to answer the primary question in this study, "What is the incremental benefit of adding RSD information to Directing, Exempting, Calling-In, and Scrapping?"

Model C calculates instantaneous overall ASM failure probability based on VID history. It is based on the analysis and modeling of all inspections performed in the California I/M program from July 1996 through April 2005. Model C calculates instantaneous overall ASM Fprobs as a function of:

[5] Four secondary models were also built.

- Vehicle description (model year, make, engine, fuel metering, emission control technology);
- The six ASM mode/pollutant cutpoints;
- Vehicle age;
- Previous-cycle initial-ASM pass/fail results;
- Time since the previous-cycle inspection.

Model D predicts the instantaneous overall ASM failure probability based on VID history, and it adds the influences of recent RSD measurements. Model D was built on the same data that was used to build Model C plus the millions of RSD measurements made in the California RSD pilot study. Accordingly, Model D contains all of the same functionalities listed above for Model C, and it includes functionalities for RSD HC, CO, and NX as measured on the road by remote sensing devices.

The primary effort in this analysis is determining the ability of Model D to improve upon the selection of vehicles for intervention activities over Model C. The reason for this is that the only difference between Model D and Model C is the inclusion of RSD information in Model D. In the analysis and modeling we have been careful to favor neither Model C nor Model D so that the incremental benefits of RSD can be revealed. We have made several breakthroughs in the analysis and modeling of VID data. These breakthroughs apply to both Model C and D equally. In addition, we have made several breakthroughs in the analysis and modeling of RSD measurements in an attempt to maximize the benefit of RSD information to the intervention strategies.

From the instantaneous overall ASM failure probabilities calculated by either Model C or Model D, we have developed methods to calculate instantaneous failed miles driven and FTP mass emissions for individual vehicles. These methods would use the individual vehicle's monthly miles driven[6] and probability of getting the next regular I/M inspection in any given month. The details of the analysis and modeling to calculate instantaneous overall ASM failure probability and the conversion of those values to failed miles driven and FTP mass emissions are described in detail in the body of this report.

The calculated value for forecasted FTP mass emissions (and of failed miles driven) for a specific individual vehicle is an estimated value calculated using the statistical techniques developed in this study. The calculated value for a specific vehicle is an estimate because it carries with it a collection of uncertainties including emissions modeling uncertainty, vehicle

[6] The calculations in this study use EMFAC monthly mileage accumulation rates, which are based on vehicle age, to determine each vehicle's monthly miles driven. An improved method would be to use the VID records of each individual vehicle to determine each vehicle's monthly miles driven.

emissions variability, individual vehicle emissions idiosyncrasies, and emissions measurement variability. Accordingly, the calculated value is our best estimate of the expected FTP emissions of the vehicle and can be thought of as the average for all vehicles with the same description, IM cutpoints, age, and IM history as the vehicle in question. Clearly, the actual FTP emissions for a specific vehicle will deviate from the average value of all such similar vehicles. However, the concept is that the sum of the expected values for a large set of vehicles will be close to the sum of the actual values for those vehicles.[7] This makes the estimated values useful because intervention activities will be applied to a large set of vehicles in the I/M fleet. From the perspective of the I/M program, the benefits of an intervention activity estimated using estimated values will approximate the real benefits achieved. Note that this application of estimated values is no different than using the now-familiar ASM Fprobs to direct vehicles; the estimated forecasted failed miles driven and FTP mass emissions are just much more useful because they quantify benefits that are important to the I/M program and the airshed. The FTP emissions calculated in this analysis are called the expected, forecasted, estimated, or most probable FTP emissions to distinguish them from emissions actually measured using the Federal Test Procedure.

Here, we provide an example for an individual vehicle that uses the results of the analysis to describe how the benefits of the different intervention activities are quantified. The example vehicle is a 1988 Ford Taurus with a 3.0 liter engine. This vehicle's previous-cycle initial test was performed on February 15, 2003 in which the vehicle failed the ASM2525 NX and passed the other five ASM mode/pollutant tests. The vehicle was repaired and four days later it passed all six ASM mode/pollutant tests and was certified. Twenty-one months later on November 22, 2004, the vehicle received an on-road RSD measurement in the California RSD pilot study. Because the vehicle received an RSD measurement, the vehicle was "brought to our attention" at that time. The date of the RSD measurement is called the decision point for this vehicle. Based on VID odometer readings the vehicle is known to drive about 1,000 miles per month. We would like to calculate the benefits that would accrue for this vehicle in the 24 months following the decision point for Directing, Exempting, Calling-In No-Sticker, Calling-In Sticker, and Scrapping. If we do this calculation for all other vehicles that were brought to our attention in

[7] We have not checked the agreement between estimated FTPs and measured FTPs on a representative set of California vehicles. However, in Table 4-9 we have checked the agreement between estimates of the California I/M fleet's total FTP emissions using EMFAC and using the methods developed in this study. Depending on the model and pollutant compared, the fleet total FTPs were typically within 50% of the EMFAC estimates. However, the purpose of this study is to estimate the <u>relative change</u> in fleet emissions from adding an RSD component to the I/M program and not to estimate the absolute total fleet emissions. Along these lines, Table 4-9 also shows that the methods developed in this study estimate the annualized benefit of the biennial I/M program as 10 to 15% of the I/M fleet's total emissions. We believe that these are reasonable estimates of the annual benefit of the I/M program.

the same month, we will have the information that can be used to prioritize vehicles for targeting for Directing, Exempting, Calling-In, and Scrapping.

Figure ES-1 and ES-2 show the backcasted and forecasted values for failed miles driven and FTP NX emissions for this vehicle from Month -21, which is the month of the previous-cycle ASM inspection in which the vehicle was failed and repaired, until 24 months after the decision point. The curves in Figures ES-1 and ES-2 are based on instantaneous ASM Fprobs using Model C, which is the VID history model without RSD information.

Figure ES-1 shows failed miles driven as a function of the months since decision. The vertical dashed line at Month 0 indicates the location of the decision point. For the time before the decision point, the failed miles driven is simply the calculated overall ASM failure probability times the number of miles the vehicle drives per month because we know from the VID records that no I/M activity occurred for this vehicle between Month -21 and Month 0.

On the other hand, after Month 0, which is the future, we do not know when the vehicle will come in for inspection. However, based on our analysis of the VID, we know the probability for any given month that the vehicle will come in for an inspection. Based on these probabilities, as well as the overall ASM failure probability and the monthly miles driven, we can calculate the failed miles driven for the case if the vehicle participates in the Normal I/M Process. This is shown in Figure ES-1 by the blue curve with the solid dots labeled NIM. This curve shows a large drop in the failed miles driven around Month 3, which is 24 months after the previous I/M inspection, which occurred in Month -21. The NIM curve is not an exactly vertical drop because we do not know exactly when the vehicle will come in for an inspection. The NIM curve also shows that after approximately Month 8 the failed miles driven for the vehicle will again increase as the vehicle ages and emissions degradation following a possible repair sets in.

If the vehicle would not continue to participate in the I/M program for the 24 months after the decision point, the failed miles driven for the vehicle is estimated to be along the black curve with the open circles labeled NoFIM meaning No Further I/M. The difference in the areas between the NoFIM curve and the NIM curve (-2777 failed miles driven/24 months) is the annual I/M benefit for this vehicle participating in the I/M program in terms of failed miles driven.

Figure ES-1. Demonstration of Failed Miles Driven Forecasting

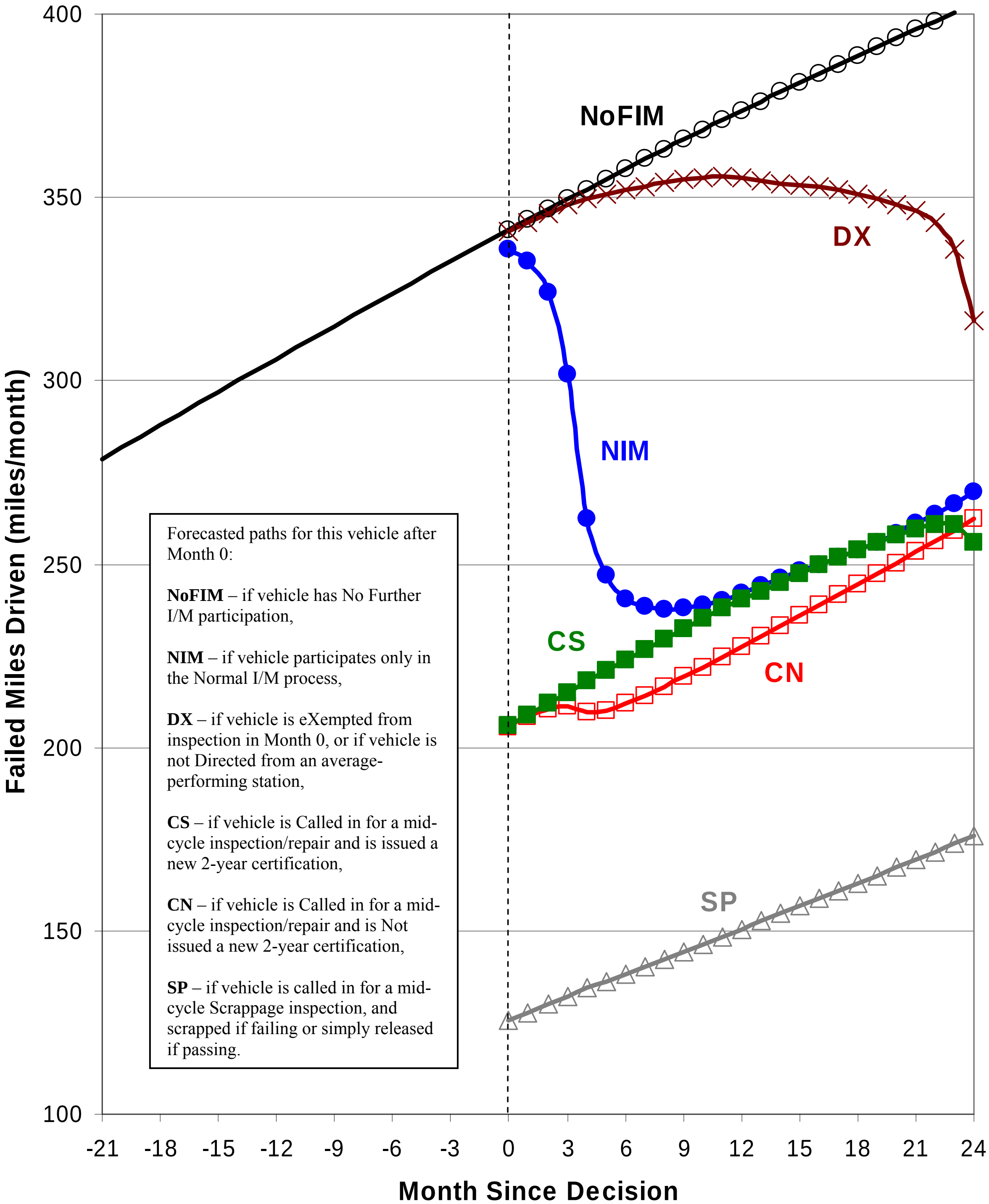
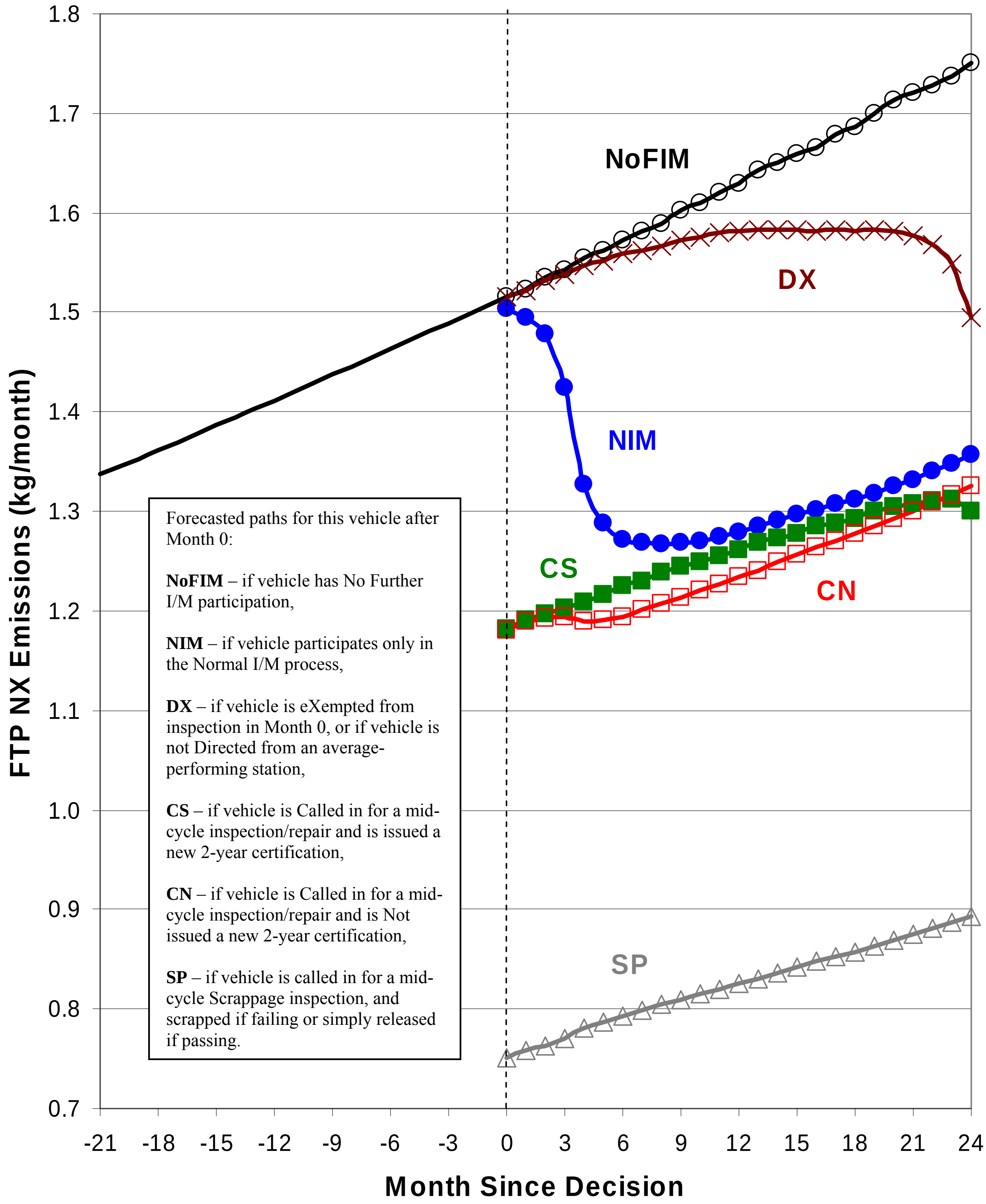


Figure ES-2. Demonstration of FTP Mass Emissions Forecasting



Now let us consider Exempting. If we would decide to exempt the vehicle in Month 0, the vehicle would not receive an ASM test in Month 0 but it would be given a two-year certification. In Figure ES-1, the brown curve with the X symbols, which is labeled DX, shows the expected result in terms of failed miles driven. The chances of failing an ASM after Month 0 increase at first. However, there is also a chance that the vehicle would come in for a change of ownership inspection or come in early for the next regular I/M inspection in Month 24 since that would be the month in which the exemption certification given in Month 0 would expire. The net effect is that the failed miles driven for Exempting is going to be higher than the Normal I/M curve but not as high as the No Further I/M curve. The difference in area between the NIM curve and the DX curve (+2167 failed miles driven/24 months) gives the increase in failed miles driven for this vehicle if it would be exempted instead of continuing to participate in the Normal I/M Process. Because this is a large area, this vehicle would likely not be ranked high in an exemption priority list.

The case for Directing also uses the NIM and DX curves. However, for Directing, the explanation and rankings are different. The logic behind Directing vehicles to high-performing stations is that high-performing stations are considered to be more accurate than average-performing stations are. Our worst fear is that an average-performing station would fraudulently pass a vehicle. The result would be that the vehicle at the average-performing station would follow the DX curve. On the other hand, we trust the high-performing station and assume that a vehicle tested there would follow the NIM curve. Thus, we would want to direct vehicles to high-performing stations when the difference between the DX curve and the NIM curve was the largest. Because the area between the DX and NIM curves (-2167 failed miles driven/24 months) in Figure ES-1 is large, this particular vehicle might be a good candidate for directing.[8]

Another intervention strategy to consider is calling the vehicle in immediately in Month 0 for a call-in ASM test. If the vehicle fails the call-in ASM test, it would be required to get a repair. Then, depending on the I/M program policy, it could either receive a two-year certification in Month 0 or it might be required to remain on its regular I/M schedule, which would mean that it would have to be retested in the vicinity of Month 3.

In Figure ES-1, the case for Calling-In Sticker is shown by the green curve with the solid squares that is labeled CS. This curve takes into account the probability that the vehicle would fail the call-in ASM test, the size of the decrease in the overall ASM failure probability at the

[8] Of course, the actual benefit of Directing is smaller than the value calculated. The reason for this is that inaccuracies occur for only some inspections at average-performing stations and not all high-performing inspections are perfect. Nevertheless, the calculated Directing benefit is adequate for ranking vehicles.

repair, and the effects of emissions degradation. The CS curve shows a general upward trend and then, at Month 24, shows a small decrease since this is the time when the vehicle would be required to get its next regular ASM test based on the new certification that it received in Month 0. The CS curve is clearly below the Normal I/M Process curve. However, it is substantially below only during the first few months after the decision point. The area between the NIM curve and the CS curve and to the right of the Month 0 dashed line (-599 failed miles driven/24 months) is the size of the benefit for Calling-In Sticker for this particular vehicle. This area is not particularly large mainly because the vehicle is likely to come in for its next regular I/M inspection in Month 3. However, for a different vehicle whose previous inspection may have been in Month -12, the area between NIM and CS would be much larger. That other vehicle would, therefore, be higher on the priority list for Calling-In Sticker.

For the case where the I/M program policy would be to not give a new certification for call-in ASMs even though they met the call-in ASM requirements, the red curve with the open squares that is labeled CN in Figure ES-1 gives the failed miles driven. For this particular example, CN is below CS for most of the time after the decision point. Accordingly, for this situation, there is a benefit for having a no-new-certification policy for call-ins for this vehicle. The CN curve shows a small downward jog in the vicinity of Month 3 because the vehicle would be eligible for a regular I/M inspection in Month 3. However, the jog is small because the chances of failing the regular I/M inspection is small since it had just met I/M requirements during the call-in ASM test just three months earlier. The benefit to be realized for Calling-In No-Sticker over the Normal I/M Process is the area between the NIM curve and the CN curve that is to the right of the Month 0 dashed line (-803 failed miles driven/24 months). Again, this is a relatively small area so this particular vehicle would not likely be high on the priority list for Calling-In No-Sticker.

The failed miles driven for the Scrapping scenario are shown in Figure ES-1 as the gray curve with the open triangles. At first the reader might think the failed miles driven for a vehicle should be zero throughout the period from Month 0 to Month 24 since the vehicle would be scrapped. This is not the case because the vehicle has only a chance of failing a scrappage ASM in Month 0. If the vehicle fails the scrappage ASM, then the failed miles driven would be zero. If the vehicle passes the scrappage ASM then, in the scenario that we have used for the calculations, the vehicle would be released without a new certification and would continue on its regular I/M schedule similar to the case for Calling-In No-Sticker. However, because the vehicle has passed the scrappage ASM in Month 0, for this vehicle it is unlikely to fail the regular ASM which would be administered in the vicinity of Month 3. Accordingly, the expected failed miles driven benefit for this particular vehicle is the area between the NIM curve and the SP curve (-2782 failed miles driven/24 months).

The benefits of the Normal I/M Process, Directing, Exempting, Calling-In No-Sticker, Calling-In Sticker, and Scrapping can also be calculated on an FTP HC, CO, and NX basis. Figure ES-2 shows the corresponding curves for the estimates of FTP NX emissions as an example.

It is important to keep in mind that this example is for a vehicle that failed its previous ASM inspection. The trends shown in Figure ES-2 suggest that the FTP emissions are lower for the NIM scenario at Month 8 than they were 24 months earlier at Month -16, which was just after the previous cycle's ASM test and repair. This might make it seem that the models are saying that the vehicle will get cleaner and cleaner as the years go by. This interpretation is not correct. Instead, the trend says that repairs induced by the I/M program tend to reduce the emissions of failing vehicles. The reason for the decrease from Month -16 to Month 8 is that the values for the NoFIM curve are on a different "knowledge" base than the values for the NIM curve. The NoFIM curve (from Month -21 to Month 24) is based on the <u>known</u> ASM2525 NX failure of this <u>specific, individual vehicle</u> in Month -21. The vehicle has higher values of FTP emissions throughout both cycles for No FIM because we <u>know</u> that it failed in Month -21. On the other hand, the values for the vehicle for the NIM scenario are based on the outcome of the vehicle's next-cycle ASM test, which could be anytime after Month 0 but is most likely to occur in Month 3. Whenever the vehicle's next-cycle inspection occurs, its results cannot be known since the test will be in the future. Since there is a possibility that the vehicle will pass the next-cycle inspection, and we know for sure that the vehicle failed the ASM inspection in Month -21, we expect that the emissions will be lower in Month 8 than they were in Month -16.

The forecasted benefits for failed miles driven and FTP mass emissions that are shown in Figures ES-1 and ES-2 are based on predictions using Model C, which is developed on VID history data. Forecasts were also made using Model D, which is based on RSD measurements as well as VID history data. The locations of the benefits curves when using Model D instead of Model C will be somewhat different. This means that the benefits estimated for each of the individual vehicles in the fleet will be different between Model C and Model D and will result in different rankings of the fleet vehicles. For the purpose of prioritizing for Directing, Exempting, Calling-In, and Scrapping, the degree to which the Model D rankings provide a better capture of measured benefits compared to Model C rankings is a direct measure of the benefit of using RSD measurements for the purpose of improving Directing, Exempting, Calling-In, and Scrapping vehicle selections.

Ranking Vehicles Using Forecasted Benefits

To answer each of the four Task 1 questions, vehicles in the analysis dataset were ranked by the benefits forecasted for each of the vehicles for the four different intervention activities. However, the benefits quantity that was used for ranking Directing, Exempting, and Calling-In was different than the quantity used for ranking Scrapping.

The ranking variables for Directing, Exempting, Calling-In Sticker, and Calling-In No-Sticker were based on the change in failed miles driven (ΔFMD) calculated for each of those situations as described for Figure ES-1. We chose ΔFMD as the ranking variable because while the goal of the I/M program is to reduce total fleet emissions, the means by which the I/M program approaches the problem is by trying to ensure that all vehicles are in an ASM-passing status at all times. The I/M program recognizes that simply minimizing the total emissions is not a practical goal because the logical conclusion of that goal is the crushing of all vehicles.

On the other hand, crushing vehicles is the stated goal of Scrapping. Accordingly, the ranking variable for selection of vehicles for Scrapping is based on the forecasted change in FTP emissions (ΔFTP) as described by the area between the NIM and SP curves in Figure ES-2. However, the ranking variable is not exactly the ΔFTP. Instead, the ranking variable is ΔFTP divided by the value of the vehicle in dollars. By ranking vehicles by ΔFTP/$, the state of California can target those vehicles for scrappage that will provide the largest decrease in total FTP emissions for the limited budget that the state has to spend on purchasing scrappage vehicles.

To summarize, the rankings in this study were produced by comparing the forecasted benefits for Models C and D differently for each intervention strategy:

- For Directing, Calling-In Sticker, and Calling-In No-Sticker, the goal was to maximize the reduction in failed miles driven.
- The goal for Exempting was to minimize the increases in failed miles driven.
- For Scrapping, the goal was to maximize the FTP reductions per vehicle value dollar.

Because there are three types of FTP emissions (HC, CO, and NX), in the study we actually ranked vehicles for Scrapping by each of the three types so that the rankings could be clearly evaluated. In future efforts, rankings of vehicles for FTP emissions could be made based on combining forecasted FTP emissions such as by HC + NX + CO/50.

Criteria Used to Evaluate Vehicle Rankings

The combination of the five types of intervention activities plus two models to forecast benefits lead to ten primary ways to rank vehicles. However, for each of the five intervention activities (Directing, Exempting, Calling-In Sticker, Calling-In No-Sticker, and Scrapping), there are only the two primary rankings: from Model C and from Model D. We need to develop evaluation criteria to compare the performances of each pair of vehicle rankings for each intervention activity.

For each vehicle ranking, we need to calculate quantities that can be used to evaluate the relative value of different vehicle rankings. The quantities that we chose for these criteria are the new and old benefits:

- Change in failed miles driven over the 24 months after the decision point (new).
- Change in FTP HC, CO, and NX emissions over the 24 months after the decision point (new).
- Fraction of targeted vehicles that fail at the decision point (old).

In our opinion, only the evaluation criteria based on the new benefit definitions are real benefits. The criterion based on the old definition of benefit is not a real benefit since it only exists for a single point in time and does not extend over the 24 months between biennial inspections. However, it is included in the evaluation of the rankings because researchers have been considering it for many years. In our opinion, its only value as an evaluation criterion is as a measure of the embarrassment for intervention activities.

Evaluation of Vehicle Rankings

In an ideal world, to perform an evaluation of the vehicle rankings, we would want an ASM emissions test and an FTP emissions test on each vehicle for each of the 24 months after the RSD measurement. Then, each of the three evaluation criteria could be calculated for each vehicle ranking. This extreme level of testing was not done in this study. In fact, no intervention testing, such as directing ASMs, exemption ASMs, call-in ASMs, or scrappage ASMs, were ever performed in this study. Except for a few special tests performed for some low-effort specialty tasks, vehicles that had received pilot study RSDs only had the opportunity to have ASM tests performed in the course of their natural progress through the I/M program. How then will we evaluate the performance of the different vehicle rankings if there are no measured data following Directing, Exempting, Calling-In, or Scrapping intervention ASM tests?

The approach we have used in this document is to evaluate, using the three evaluation criteria, the vehicle rankings based on Models C and D by calculating the three evaluation criteria using Model D.

There are a couple of problems with this approach. First, by using modeled values to calculate the evaluation criteria, we are assuming that the modeled values are a true representation of what would actually be measured from 24 monthly ASM and FTP tests on all of the vehicles in the dataset. Second, the evaluation criteria for a vehicle ranking that is also used as the basis for the evaluation criteria will have an unfair advantage over the vehicle ranking that is not based on the model that is used to calculate the evaluation criteria. For example, if vehicles are ranked for Directing by Model C and Model D using the evaluation criterion ΔFMD calculated by Model D, then Model D will always beat Model C for the ΔFMD criterion.

When Model D is used to calculate the evaluation criteria, the vehicle rankings based on Model D will tend to be better than the rankings based on model C. In this evaluation situation, the real amount that the Model D rankings are better than Model C rankings can be no larger than the difference by this method. Thus, the difference in benefits of Model D rankings over Model C rankings (when Model D is used to calculate the evaluation criteria) is an upper limit on the amount that adding RSD information to VID information would increase the benefits.

Table ES-1 shows the difference in estimated benefits for Model D and Model C rankings when Model D is used to calculate the evaluation criteria. For each intervention activity, we tabulate the benefits of Model C (VID History) and Model D (VID History + RSD) at one chosen fleet targeting percentage. The influence of adding RSD information can be seen by looking at the change in the benefit when going from ranking by Model C to Model D while taking into account the benefit for 100% targeting. A negative sign indicates a decrease in the quantity. For change in failed miles driven and FTP mass emissions, the smaller (taking sign into account) is the better number. For fraction failing at the decision point, the larger is the better number. For clarity, we have made the better numbers bold in the table.

The amount that the Model D benefit is better than the Model C benefit relative to the full range of benefit available represents the maximum relative improvement that adding RSD could make. For example, consider FTP HC mass emissions for Directing. Selection by Model C would decrease FTP HC mass emissions over 24 months by 7.6%. Selection by Model D would decrease FTP HC emissions over 24 months by 8.6% – an improvement of 1.0%. We regard this as a small improvement since if 100% of the vehicles were targeted for Directing, the most that FTP HC emissions over 24 months would be reduced is 11.3%.

Table ES-1. Summary of Effect of Adding RSD Information on Intervention Activity Benefits

Intervention Activity	Benefit/Model Used for Vehicle Ranking	Percent Fleet Targeted (%)	Change in Fleet Failed Miles Driven (% of the Normal I/M Process Fleet FMD)	Change in Fleet FTP Mass Emissions (% of the Normal I/M Fleet FTP Mass Emissions)			Targeted Vehicles Failing an ASM at the Decision Point (fraction)
				HC	CO	NX	
Directing		0%	0.0	0.0	0.0	0.0	1.00
	DI ΔFMD by C	40%	-15.7	-7.6	-5.0	-4.4	0.17
	DI ΔFMD by D	40%	**-17.5**	**-8.6**	**-5.6**	**-4.8**	**0.20**
		100%	-20.2	-11.3	-7.6	-7.3	0.10
Exempting		0%	0.0	0.0	0.0	0.0	0.00
	EX ΔFMD by C	20%	0.76	0.59	0.48	0.66	0.035
	EX ΔFMD by D	20%	**0.10**	**0.34**	**0.29**	**0.45**	**0.020**
		100%	20.2	11.3	7.6	7.3	0.102
Calling-In No-Sticker		0%	0.0	0.0	0.0	0.0	1.00
	CN ΔFMD by C	5%	-3.2	-1.02	-0.57	-0.55	0.33
	CN ΔFMD by D	5%	**-3.6**	**-1.21**	**-0.65**	**-0.64**	**0.40**
		100%	-8.4	-4.2	-2.9	-2.8	0.10
Calling-In Sticker		0%	0.0	0.0	0.0	0.0	1.00
	CS ΔFMD by C	5%	-2.8	-0.85	-0.45	-0.44	0.33
	CS ΔFMD by D	5%	**-3.2**	**-0.97**	**-0.50**	**-0.49**	**0.39**
		100%	-5.9	-2.46	-1.64	-1.51	0.10

Table ES-2 shows the comparison of estimated benefits for Model C and Model F rankings when Model D is used to calculate the evaluation criteria. For each intervention activity, the table contains the benefits of Model C (VID History) and Model F (RSD) at one chosen fleet targeting percentage. This table reveals which set of information – VID History or RSD measurements – provides the better ranking of vehicles for benefits. The competition can be judged by taking into account the benefit for 100% targeting. As usual, a negative sign indicates a decrease in the quantity. For failed miles driven and FTP mass emissions, the smaller (taking sign into account) is the better number. For fraction failing at the decision point, the larger is the better number. For clarity, we have made the better numbers bold in the table.

Table ES-2. Summary of Competition Between VID History Information and RSD Information for Intervention Activity Benefits

Intervention Activity	Benefit/Model Used for Vehicle Ranking	Percent Fleet Targeted (%)	Change in Fleet Failed Miles Driven (% of the Normal I/M Process Fleet FMD)	Change in Fleet FTP Mass Emissions (% of the Normal I/M Fleet FTP Mass Emissions)			Targeted Vehicles Failing an ASM at the Decision Point (fraction)
				HC	CO	NX	
Directing		0%	0.0	0.0	0.0	0.0	1.00
	DI ΔFMD by C	40%	**-15.7**	-7.6	**-5.0**	**-4.4**	0.17
	FprobDP by F	40%	-15.0	**-7.8**	-5.0	-4.1	**0.21**
		100%	-20.2	-11.3	-7.6	-7.3	0.10
Exempting		0%	0.0	0.0	0.0	0.0	0.00
	EX ΔFMD by C	20%	**0.76**	**0.59**	**0.48**	**0.66**	0.035
	FprobDP by F	20%	0.84	0.81	0.64	0.85	**0.014**
		100%	20.2	11.3	7.6	7.3	0.102
Calling-In No-Sticker		0%	0.0	0.0	0.0	0.0	1.00
	CN ΔFMD by C	5%	**-3.2**	**-1.02**	**-0.57**	**-0.55**	0.33
	FprobDP by F	5%	-1.4	-0.87	-0.47	-0.29	**0.44**
		100%	-8.4	-4.2	-2.9	-2.8	0.10
Calling-In Sticker		0%	0.0	0.0	0.0	0.0	1.00
	CS ΔFMD by C	5%	**-2.8**	**-0.85**	**-0.45**	**-0.44**	0.33
	FprobDP by F	5%	-1.1	-0.56	-0.28	-0.17	**0.44**
		100%	-5.9	-2.46	-1.64	-1.51	0.10

The table shows that for 15 of 16 cases, Model C provides better failed miles driven and FTP mass emissions benefits than Model F. For the fail fraction at the decision point the reverse is true – Model F is better than Model C. Thus, in the case of competition between Model C and Model F, there is a trade-off: Model C captures more failed miles driven and more emissions over the 24 months after the decision point, while Model F gets more fails at the one-point-in-time decision point. We believe that emissions are more important than the fail rate at the decision point, and therefore, we favor Model C over Model F. However, the results in Table ES-1 indicate that if both VID information and RSD information are used together (Model D), the emissions capture is even better than when either is used alone.

In the case of Scrapping, we ranked the 69,629 vehicles in the dataset based on expected change in FTP HC (rankings by ΔFTP CO and ΔFTP NX were also evaluated) mass emissions over 24 months divided by the estimated value of the vehicle. We then "purchased" the most attractive candidates in each of the Model C and Model D rankings using a $50,000 budget. For the Model C ranking, 219 vehicles were purchased for $50,000. The estimated FTP HC, CO, and NX emissions captured over 24 months were 9.2, 108, and 4.6 metric tons. For the Model D ranking, 172 vehicles were purchased for $50,000. The estimated FTP HC, CO, and NX emissions captured over 24 months were 10.5, 116, and 4.8 metric tons. Thus, Model D allowed slightly more mass FTP emissions to be captured through Scrapping.

We also ranked vehicles for Scrapping using the overall ASM failure probability at the decision point using Model F, which is based solely on RSD measurements. For this ranking, 27 vehicles were purchased for $50,000. The estimated FTP HC, CO, and NX emissions captured over 24 months were 1.8, 15.7, and 1.0 metric tons – substantially less than the emissions captured by Models C and D.

It will be the job of the implementation report, which will use the results from this report, to determine whether the slightly higher fleet FTP emissions capturable by adding RSD information to intervention activities is worth the expense of performing RSD measurements throughout the state of California.

1.0 Overall Analysis Approach

It's what happens in the 24 months after the I/M inspection that is important to an I/M program's effectiveness. Up to this point in the development of I/M programs, intervention in I/M programs with supplemental vehicle-selection strategies has been focused on whether the vehicle passes or fails the I/M test at the time it is inspected. The problem with this strategy is that, as soon as the vehicle leaves the inspection facility, changes rapidly occur. Because no methods had been developed to forecast the changes that occur after an I/M inspection, there was no way to select vehicles for I/M improvement strategies in a manner that considered the future. In this document, we present methods that can be used to forecast overall ASM failure rates and even FTP mass emissions for individual vehicles 24 months after the vehicles have been inspected in the I/M program. These predictions are based on vehicle description, model year, VID history, and/or RSD measurements using several mathematical and statistical techniques new to the I/M field.

The goal of this task is to find the combinations of information from VID history, RSD measurements, and other information that will most benefit the I/M program when used under different supplemental vehicle-selection strategies in comparison with the Normal I/M Process. The supplemental vehicle-selection strategies that are considered in this report are:

- Directing vehicles to high-performing stations just before their biennial anniversary,
- Exempting vehicles from their biennial anniversary inspection,
- Calling-in vehicles mid-cycle but not giving them a new 24-month certification at the time of the call-in ASM,
- Calling-in vehicles mid-cycle and giving them a new 24-month certification for completion of the call-in ASM, and
- Scrapping vehicles.

To answer the questions in this study, we needed to develop a method to optimally select vehicles for Directing, Exempting, Calling-In, and Scrapping, to use different combinations of vehicle information, and to quantify the benefits of applying the different strategies versus leaving the vehicle in the Normal I/M Process.

At some point in the I/M-program life of the vehicle, I/M program staff may want to decide whether an individual vehicle should continue in the Normal I/M Process or whether they should intervene in the Normal I/M Process to cause the vehicle to be directed, exempted, called-in, or scrapped. For whatever type of intervention is contemplated, the choice will always be between letting the vehicle progress through the Normal I/M Process and intervening. When making a decision to intervene, it is important to quantify the benefits of the intervention option with respect to the Normal I/M Process option for the time period over which the decision will have an impact. In this study, since California's I/M program is biennial, we assumed that the impact period is the 24 months after the decision.

Several steps are required in this analysis to answer the questions of interest to the California Air Resources Board and the California Bureau of Automotive Repair. This document describes how each of these steps has been accomplished.

- **Select a question to answer** - The questions to be answered are for Directing, Exempting, Calling-In, and Scrapping.

- **Select a vehicle ranking method** - We have evaluated three ranking methods including the traditional one, which we believe is obsolete, and two new methods that look at the 24 months after the decision.

- **Select a failure probability model to evaluate** - To determine the value of different types of information, we have developed six different failure probability models that can be used to prioritize vehicles for selection.

- **Rank the vehicles in the pilot dataset to answer the chosen question -** New methods for ranking vehicles that are specific to the question asked have been developed. Time is a key variable. The ranking methods are probabilistic in nature.

- **Calculate the benefits** - We have further developed methods to evaluate the benefits of the ranking. We calculate the benefits to arrive at measures of performance for each combination of failure probability model and ranking method. A comparison of the measures of performance for the different sources of data reveals the benefit of including RSD measurements in the existing I/M program.

Section 2 describes the development and capabilities of the six new ASM failure probability models. The section describes new methods for using historical VID data, for analyzing RSD measurement data, and for estimating FTP mass emission rates. Section 3 describes the development of other information that was needed to forecast ASM failure probabilities for specific questions. The most important of these are the I/M completion probabilities, which are as important to forecasting as the ASM failure probabilities are. Section 4 describes the approach for ranking vehicles for the different questions in the study. This includes the description of the one traditional and two new individual vehicle ranking criteria that are used. This section also contains the detailed descriptions of how the various failure probabilities and I/M completion probabilities are combined in a time framework to arrive at ranking criteria that are specific to the individual questions and for individual vehicles. Section 5 describes the approach for using the vehicle rankings calculated in Section 4 to evaluate the benefits of the six ASM failure probability models and the three ranking methods for Directing, Exempting, Calling-In, and Scrapping.

2.0 ASM Failure Probability Models

ASM failure probability models using different types of vehicle information on individual vehicles were built in this study to:

- Calculate the overall ASM failure probability, and
- Calculate the expected FTP HC, CO, and NX emission rates (g/mile).

The models that are most useful have a time dependence so that failure probabilities can be forecast into the future. Forecasting the future for individual vehicles is important since the benefits to be gained from an I/M program accumulate after I/M-induced changes (pre-inspection repairs and repairs made to get a vehicle to pass a follow-up inspection) are made to the vehicles. Because of emissions degradation following repairs, emissions changes seen at the time of an inspection-and-repair event are only a crude indication of the benefits that might be realized in the future. Consequently, being able to forecast the status of a vehicle between I/M inspections is a capability that is important to choosing the vehicles that are to receive a particular intervention. By intelligently selecting vehicles for intervention, the efficiency of the I/M program can potentially be improved.

We have found that all of the needs of this study for forecasting failure probabilities and emissions can be met by developing and using ASM failure probability models. The development of these models begins with the consideration of the traditional ASM failure probabilities known as Fprobs. These traditional Fprobs were developed years ago on the California VID. By bringing several mathematical and statistical techniques to the analysis of the VID and by adding the new RSD data collected in this study and new techniques for analysis of that data, we have been able to develop six new Fprob models that we will use to answer the questions in this study.

In the subsections below, we will review the capabilities of the traditional Fprobs, describe the six ASM failure probability models that we developed, and describe the techniques that we used to develop the models from the VID and RSD data. Finally, we will present a graphical illustration of the functionalities that one of the Fprob models provides.

2.1 Review of Capabilities of Traditional ASM Failure Probabilities

Traditional Fprobs serve as the starting point in the development of the ASM failure probability models developed in this study. We will begin with a review of the advantages of traditional Fprobs and the problems that are associated with them. Traditional Fprobs came about because of a need to anticipate whether vehicles would pass or fail an I/M inspection before the vehicle arrived at the inspection station. Fprobs have been developed for various I/M program emissions tests including two-speed idle, IM240, IM147, and ASM including Fprobs for the different modes of inspection tests such as the six mode/pollutant tests of the ASM.

The advantages of traditional ASM Fprobs are described below:

Easy to calculate – The traditional ASM Fprobs were relatively easy to calculate. They were based on the simple concept of counting the number of passes and fails of an I/M program emissions test for all of the vehicles of a given description based on data collected in the VID. If the VID showed that 10% of the vehicles of a particular description failed the emissions test, the Fprob for that vehicle description was 0.10.

Based on VID data – The Fprobs calculated by this method were based on the VID data. This means that they were based on data taken in the same circumstance, that is, I/M, in which they would be applied. In addition, since the VID is a large dataset, the uncertainties in the Fprob values were relatively small.

Specific to vehicle descriptions – Because the Fprobs were calculated separately for different vehicle descriptions, for example a given combination of model year, make, model, engine, and emission control system technology, the Fprobs were able to capture some of the idiosyncrasies that were specific to individual vehicle descriptions. For example, some vehicle descriptions might be more prone to emission control system degradation than other vehicle descriptions.

Probabilistic – The whole Fprob concept recognizes that it will never be possible to forecast with certainty whether a vehicle will pass or fail a future I/M inspection or to predict its ASM or FTP emissions exactly. The inability to forecast ASM failures perfectly is tied to the large variability in individual vehicle emissions as a function of time, the variability in emissions of vehicles of the same description, the variability in vehicle usage and repair histories, and the variability in the emissions measurement process. Nevertheless, the use of traditional Fprobs has demonstrated that the ability to calculate the probability that a vehicle will fail a future ASM inspection is useful.

Useful – Traditional Fprobs have been used for several years in different situations, for example, to clean screen and dirty screen vehicles just before their I/M anniversary, or to estimate relative I/M inspection station accuracy. Results have been good and Fprobs have proven to be useful.

A number of problems with traditional Fprobs limit their value:

Vehicle aging – Traditional Fprobs are calculated from VID data without regard to the age of the vehicle at the time of its inspection. While, in general, inspection failure probabilities increase as vehicles age, traditional Fprob values are constant for all vehicle ages. Thus, vehicle aging causes traditional Fprobs to "go stale" as calculated Fprob values get older. In the past, this aging effect of Fprob values has caused traditional Fprobs to be re-calculated on a regular basis using the most recent portion of the VID.

ASM cutpoint – Traditional ASM Fprobs have also been calculated without regard to the ASM cutpoints used to determine if a vehicle is a pass or fail. California has periodically tightened ASM cutpoints. Clearly, vehicles will have a higher probability of failing an ASM test if the cutpoint is at a lower value. Thus, tightening cutpoints has the tendency to increase failure probability. This would not be a problem if the cutpoints were constant over the portion of the VID used to calculate the Fprobs. In the past, this has presented a dilemma to the analyst calculating Fprobs. Either a small portion of the entire VID with constant cutpoints is used to calculate Fprobs, or the entire VID is used and the effect of the cutpoints is averaged or "smeared."

Previous-cycle inspection results – Traditional ASM Fprobs do not take into account the result of the previous I/M inspection for the vehicle. We know that, in general, vehicles that have failed a previous inspection are more likely to fail later inspections than vehicles that have passed a previous inspection.

Time since previous inspection – Traditional Fprobs also do not take into account the time since the previous inspection. It seems reasonable that a vehicle that failed its initial inspection, was repaired, and passed its final inspection yesterday would be more likely to pass a follow-up ASM inspection than a vehicle that failed initially, was repaired, and passed its final inspection two years ago. This time effect can also be viewed as the emissions degradation following a repair to a vehicle. We expect that the rate of emissions degradation will be different for different types of vehicles and for different vehicle ages.

Emissions – While in general, vehicles with higher traditional Fprobs would be expected to have higher emissions, estimating ASM, IM240, or FTP emissions from traditional Fprobs is not expected to be possible. Using emissions measurements that are recorded in the VID is problematic since most measurements recorded for vehicles that pass the inspection are on a fast-pass basis. Fast-pass values tend to be biased high in comparison with the emissions concentrations that would be obtained for a full-duration ASM test.

RSD measurements – Traditional Fprobs did not take into account any supplemental measurements of emissions concentrations on individual vehicles such as RSD measurements. Clearly, for two vehicles that have the same traditional Fprob, the vehicle with the higher RSD measurement values would tend to be more likely to fail an emissions test.

On-road status – Traditional Fprobs are a measure of the probability that vehicles will fail an ASM test in the normal I/M inspection situation where the vehicle owner knows that his vehicle will be undergoing an inspection. California I/M program staff expects that, in many instances, owners in this situation will perform pre-inspection repairs, such as tune-ups, on their vehicles before taking them to be inspected. Consequently, the failure rates for the normal I/M program are lower than the failure rates observed during roadside pullover tests for which vehicle owners have no advance notice that their vehicle will receive an ASM emissions inspection. Because traditional Fprobs are based on an analysis of VID data, they do not reflect failure probabilities of vehicles in normal on-road driving situations.

With the exception of on-road status, the best ASM failure probability model (Model D) developed in this study addresses all of traditional Fprob problems listed above while maintaining all of their advantages. The subsections that follow describe how these enhanced capabilities were achieved.

2.2 Description and Characteristics of Fprob Models

For this study, we developed six ASM failure probability models to answer the questions of interest. Table 2-1 shows the important features of each of the six models. The models are used to calculate the overall ASM failure probability of individual vehicles using information from RSD measurements and/or VID history. The specific functional form and coefficients for the models or examples of coefficients for the models are given in Appendices A through F for the six models. The models for RSD linearization in Appendix G support Models D, E, and F.

The first two lines of Table 2-1 indicate the sources of data for building the individual models. Models A, B, and C use only California VID data. Models E and F use only pilot RSD data. Model D uses both California VID data and pilot RSD data.

The functionalities of the six models were chosen to answer the questions in the study or to provide simplistic models for reference purposes. The second group of rows in Table 2-1 shows the inputs that affect each of the six models that were developed in this study.

Table 2-1. Attributes of ASM Failure Probability Models

	Model					
	A	B	C	D	E	F
Input Data Source						
California VID	1	1	1	1	0	0
Pilot RSD dataset	0	0	0	1	1	1
Inputs						
Metering_Emission Control System	0	1	1	1	0	0
Make_CarTrk	0	1	1	1	0	0
Engine	0	1	1	1	0	0
Model Year	1	1	1	1	0	0
Age	0	0	1	1	0	0
Previous-Cycle Initial-Test Result	0	0	1	1	0	0
Time Since Previous Cycle	0	0	1	1	0	0
ASM Cutpoints	0	0	1	1	1	0
RSD	0	0	0	1	1	1
Model Characteristics						
Mimics vehicle-description idiosyncrasies	0	1	1	1	0	0
Calculates time-constant ASM Fprobs	1	1	0	0	1	1
Forecasts time-varying ASM Fprobs	0	0	1	1	0	0
Uses recent vehicle RSD measurements	0	0	0	1	1	1
Handles changing cutpoints	0	0	1	1	1	0
Forecasts ASM mode/pollutant concentrations	0	0	1	1	0	0
Models vehicle aging gracefully	0	0	1	1	0	0
Explicitly quantifies effect of repairs	0	0	1	1	0	0
Quantifies effect of emissions degradation	0	0	1	1	0	0
Quantifies the influences of station performance	0	0	0	0	0	0
Quantifies effects of multiple RSDs	0	0	0	0	0	0
Probabilities contain variability influences	1	1	1	1	1	1

Three key models were created specifically to answer the study questions. These are Models C, D, and E. Model C is the most elaborate model in this study that uses only VID history information. Model E uses only RSD measurements and the ASM cutpoint of the vehicle in question. Model E therefore uses no VID history information. Model D is the most elaborate model in the study and uses both VID history and RSD measurements.

The performance and comparison of performances among these three models can be used to answer the questions in the following manner. Model C will demonstrate the benefits for using VID history information alone. Model E will be able to demonstrate the benefits of using RSD measurements alone. Model D will be able to demonstrate the benefits of using VID and RSD measurements together. A comparison of the performance of Model D against Model C will show the benefits of adding RSD measurements to VID history. A comparison of Model D performance against Model E will show the benefits of adding VID information to RSD measurements.

Three other models were created to assist in evaluation of model performance. Models A, B, and F are models that are simpler than C, D, and E. Model F is similar to Model E, however, Model F uses only RSD measurements and does not use ASM cutpoints. We believe that the inclusion of ASM cutpoints in a model that contains RSD measurements makes sense and is conceptually important. This can be demonstrated with a simple example. Suppose two vehicles of the same description have identical RSD measurements. In this case, the vehicle with the lower ASM cutpoints will be more likely to fail the ASM emissions test. Model E will have the capability of making this distinction and Model F will not. Model B is simply a special case of Model C where the effects of vehicle age, previous-cycle initial-test results, time since previous cycle, and ASM cutpoints have been turned off. Otherwise, the model coefficients are the same in Model B as in Model C for corresponding combinations of vehicle description and model year. Model B is similar to traditional Fprobs since the Fprobs are simply a function of vehicle description and model year. Model A is a very simple model in which the overall ASM failure probability depends only on the model year of the vehicle.

The last set of rows in Table 2-1 shows a comparison of the different characteristics of the six models:

- Because individual models were built for different vehicle descriptions for Models B, C, and D, those models mimic the vehicle-description-specific idiosyncrasies of different vehicle descriptions. On the other hand, Models A, E, and F are generic with regard to vehicle description. That is, those models apply to all light-duty gasoline vehicles – regardless of vehicle description.

- Because only Models C and D use inputs for vehicle age and time since the previous-cycle test, only Models C and D can forecast ASM failure probabilities as a function of time in the future. For the other four models, forecasted ASM failure probabilities are constant with time.

- Because only Models D, E, and F use recent vehicle-specific RSD measurements, only those models take advantage of recent vehicle-specific emissions information. On the other hand, Models D, E, and F are required to have RSD information. Accordingly, if RSD information is not available on a vehicle, Models D, E, and F cannot be used. The other three models, A, B, and C, do not require RSD information and although those models cannot take advantage of RSD measurements, Models A, B, and C can be applied to almost all vehicles in the fleet.

- Because Models C, D, and E have the full functionality of all six ASM mode/pollutant cutpoints, these models contain the influences of changing ASM cutpoints in the past and in the future. Since the other three models do not contain ASM cutpoint functionality, the effect of cutpoint is "smeared" in the model predictions and will cause an error in predictions if cutpoints in the future are substantially different than the cutpoints in the model training dataset. As shall be shown in the following subsection, models that contain ASM cutpoint functionality can be used to forecast ASM mode/pollutant concentrations and FTP mass emissions. Thus, Models C, D, and E can be used to estimate ASM concentrations and FTP mass emissions whereas the other models cannot.

- Because Models C and D contain vehicle aging functionality, those models will be able to estimate ASM failure probabilities that are robust over a longer time. This should result in models that will not need to be rebuilt as frequently as Models A, B, E, and F which do not contain vehicle aging functionality.

- Because Models C and D contain explicit functionalities for the effects of the previous-cycle initial-test pass/fail result, these models explicitly quantify the effects of previous-cycle repairs on future ASM failure probabilities. The other models do not have this characteristic.

- Models C and D contain explicit time dependence of the ASM failure probability on the time since the previous I/M cycle. Therefore, these models quantify the effect of emissions degradation following either an initial pass for an ASM inspection or an initial fail that is followed by a repair and a subsequent pass. In addition, because both Models C and D are vehicle-description specific, the functionality for the effects of emissions degradation are specific to individual vehicle descriptions.

- None of the models use station performance inputs. Therefore, the Fprobs predicted by the models represent the results expected for an average inspection station in the California I/M system.

- The dataset that was used to build the models contained some records for vehicles that received multiple RSD measurements. When building the models, we treated these records as if they had been obtained on separate, but identical, vehicles. Thus, the models that use RSD inputs provide failure probabilities based on a single RSD measurement.

- All of the models calculate the probability of failing an ASM emissions inspection at an average California I/M station. One of the advantages of using ASM failure probabilities, rather than ASM concentrations, is that probabilities inherently reflect the emissions variabilities associated with the station ASM measurement. These include the emissions variability of individual vehicles, ASM instrumental and procedural variability, and differences in ASM accuracy among I/M stations. The calculated probabilities also include the effects of the various types of variabilities that are present in the inputs on which each of the models is built. For example, the probabilities produced by Model D are influenced by, and therefore carry with them, the variabilities associated with RSD measurements, as well as by the station ASM variabilities. All of this means that the modeling approach used in this study accounts for the various types of variabilities including the emissions variability of vehicles.

Overall, we see that the six models created for this study represent a wide range of functionalities from the simplest in Model A, which uses just model year, to the most complex, Model D, which uses many pieces of VID history information as well as RSD measurements. Clearly, Models C and D are more complex than Models A and F. Another section of this report will investigate whether this additional level of complexity translates into greater potential improvements for the California I/M program.

2.3 Solving the Fast-Pass Bias Problem

One of the traditional problems with analyzing VID data is that ASM concentrations determined using fast-pass tests, which make up the bulk of the VID since most vehicles pass, are biased. The reason for this is that as soon as the instantaneous emissions concentrations for HC, CO, and NX for the ASM mode test go below the fast-pass threshold, the mode test is almost immediately terminated. Because in California the fast-pass thresholds are at the ASM cutpoint concentrations, there is a tendency for fast-pass results to be slightly below the ASM cutpoints for the vehicle. If the test had lasted for the full duration of the mode test, the ASM pollutant concentrations would tend to be lower. Using ASM concentrations from fast-pass tests would normally, therefore, introduce a bias in any models that are built.

In this study, we developed a solution to the fast-pass concentration bias problem. Rather than using ASM concentrations in model building, we simply used the pass/fail results for the six ASM mode/pollutants. We assumed that a vehicle that fast-passed an ASM mode test would have passed the full-duration ASM mode test. Accordingly, all of the models built in this study are based on the pass/fail results of the ASM tests without fear of bias introduced by the fast-pass technique. Since pass/fail results are the same source of information used for calculation of traditional ASM Fprobs, the models for this study are built on the same type of ASM results.

In this study, the method for calculating Fprobs differed from the counting technique used for traditional Fprobs. The same procedure as for traditional Fprobs <u>was</u> used for Model A where the overall failure probability is determined solely by the model year of the vehicle. The VID data was sorted by vehicle model year and the fraction of vehicles that fail divided by the total number of vehicles tested for each model year was calculated. However, because Models B, C, D, E, and F involved continuous variables such as ASM cutpoint, vehicle age, and RSD measurements, a simple counting scheme such as that used for traditional Fprobs and Model A would not take advantage of all of the information in the data.

Instead, we used a standard statistical technique known as logistic regression. A description and an example of logistic regression are provided from a recent project in Appendix H. Logistic regression is one of several techniques that can be used to calculate the probability of failing a future ASM based on a set of independent variables, which in this study are the VID history and/or the RSD measurements for an individual vehicle. We chose to use logistic regression to build these models because it is commonly used, it is available in SAS, and it was found to fit the trends in the data quite well as demonstrated by lack-of-fit tests performed on each regression. The use of logistic regression as applied to the ASM pass/fail data in the VID neutralizes the issue of bias in fast-pass ASM concentrations.

2.4 Calculating Overall ASM Fprob from ASM Mode/Pollutant Fprobs

We need to be able to calculate the overall ASM probability using each of the six models that were created in this study. The different models will have different functionalities as described in Table 2-1. One of the early problems in the development of these models was to determine the functional form of the models so that coefficients could be estimated using logistic regression. We saw two approaches that could be used to build the models.

In the first approach, a dataset could be created that contained all of the overall ASM pass/fail results. These would serve as the model's dependent variable. For each of these observations we would also have all of the independent variables such as all three RSD measurements, all six ASM mode/pollutant cutpoints, vehicle age, time since the previous-cycle, all six previous-cycle initial-test mode/pollutant pass/fail results, and model year. Then, a model could be built to predict the overall ASM failure probability as a single function of all of the independent variables. The problem with this approach is that the model statement has many coefficients to determine, the functionality of many of the independent variables is unknown, and several of the independent variables have multiple co-linearities with each other. In addition, strong interactions among the independent variables that influence the overall ASM failure probability are expected.

The second approach, which we chose and have been using for a few years in other studies, instead builds models for each of the six ASM mode/pollutants. In this approach, the response variable is only one of the ASM mode/pollutants, for example, ASM 2525 HC. The independent variables are selected to be only those that are judged to be important to the response variable based on previous information and/or regression analysis. For example, we would expect that the most important independent variables for ASM 2525 HC would be RSD HC, ASM 2525 HC cutpoint, vehicle age, time since the previous cycle, and previous-cycle initial-test ASM 2525 HC pass/fail result. Thus, by limiting the response variable to just one mode/pollutant, the functional form of the model and the number of coefficients to be determined are more easily handled.

However, another problem then arises. Once all six ASM mode/pollutants are modeled, how should their predicted results be combined to arrive at the overall ASM failure probability? If the six ASM mode/pollutant probabilities were independent, then we could combine them using simple probability combining rules for independent probabilities. However, for ASM mode/pollutant probabilities, we know the probabilities are not independent. For example, the probability that a vehicle will fail its ASM 2525 HC and the probability it will fail its ASM 5015 HC are expected to be highly correlated. The same would be true for both modes of each of the other two pollutants. In addition, we would expect the failure probabilities for HC and CO in the same mode to be correlated since both pollutants tend to be elevated when combustion stoichiometry is rich. We also expect that failure probabilities for NX will tend to be negatively correlated with probabilities for HC and CO since rich operation causes HC and CO to be elevated and NX concentrations to be lowered. All of these dependences among ASM mode/pollutant failure probabilities can be demonstrated by examination of traditional ASM mode/pollutant Fprobs.

While it is possible to combine dependent probabilities using covariance matrices, a simpler approach is to build the appropriate conditional and unconditional passing probabilities for the six ASM mode/pollutant tests and then to combine them using the standard probability combination equations for dependent probabilities. These relationships are standard and exact. Appendix I gives the equations and provides an example from a recent study to demonstrate how to combine non-independent probabilities.

To apply this technique to the models in this study, it was necessary to outline the entire set of ASM mode/pollutant models and how they would be combined before the actual models were built. Properly using the combining relationships involves two steps. In the first step, the training dataset is subsetted according to the conditional mode/pollutant to be modeled. Once the modeling has been performed on all of the conditional and unconditional mode/pollutant probabilities, the second step is to combine them using the proper relationship. The following paragraph uses Model F as an example.

Equation F-1 in Appendix F shows the proper probability relationship for determining the overall failure probability as a function of the three passing probabilities for HC, CO, and NX. In this case, the passing probabilities are determined using only RSD measured concentrations. The passing probability for ASM HC, P_{HC}, is given by Equation F-2 with Equation F-5 having the expression that is made up of the RSD measurements and the appropriate coefficients as determined from the regression. This model was determined by logistic regression on all of the paired observations that contained RSD HC, CO, and NX as the independent variables and the ASM HC mode result as the dependent variable. The second factor in Equation F-1 for the passing probability for ASM CO given that ASM HC already passed, P_{CO} | HC pass, was determined in a similar manner. However, the dataset included only those observations where ASM HC was a pass. The result of that regression is provided by Equations F-3 and F-6. In a similar manner, the passing probability expression for ASM NX given that ASM HC and ASM CO already passed, P_{NX}|HC,CO pass, was regressed on the subset of the dataset in which ASM HC and ASM CO both passed. The results are given by Equations F-4 and F-7.

This approach, which uses conditional and unconditional passing probability models to provide failure probability models using an expression similar to F-1, has been used several times in the construction of Models B, C, D, E, and F. However, the exact expressions differ from model to model depending on the needs of the models. It is important to understand that the combining of probabilities as in Equation F-1 is exact.

This approach is used to get the overall ASM failure probabilities from the ASM pollutant passing probabilities in Equations B-1, C-1, D-1, E-1, and F-1. The method is also used to get the ASM pollutant failure probabilities from the ASM mode/pollutant passing probabilities as in Equations B-11, B-12, and B-13 and Equations C-11, C-12, and C-13 and Equations E-11, E-12, and E-13.

Several of the models also require deriving conditionalized ASM pollutant passing probabilities from ASM unconditional failing probabilities. To make these conversions, logistic regression was used to determine regression coefficients for the logits of the ASM pollutant unconditional failing probabilities. In this instance, we do not know of any way to combine the unconditional pollutant probabilities in an exact manner. However, by using logistic regression, we arrive at an estimated conditional ASM pollutant passing probability that, in the domain of training data, is unbiased even though it may not be exact.

An example of this conditionalizing step is seen for Model E. The ASM pollutant failing probabilities are output as a result of Equations E-11, E-12, and E-13. However, to calculate the overall failure probability for Model E, as in Equation E-1, the unconditional passing probability for HC and the conditional passing probabilities for CO and NX must be calculated. This is accomplished by the regressions that result in Equations E-2, E-3, and E-4. Equations E-5, E-6, and E-7 show the model statements and coefficients that are derived by the regression. The independent variables for each of the regressions are determined by taking the logits of the failing probabilities for ASM HC, CO, and NX as shown in Equations E-8, E-9, and E-10.

Similar conditionalizing models are used for Models B and C as shown in Equations B-2, B-3, and B-4 and C-2, C-3, and C-4 to derive conditionalized ASM pollutant passing probabilities from ASM unconditional failing probabilities. In addition, for Model D, the same technique is used in Equations D-2, D-3, and D-4 to derive conditionalized ASM pollutant passing probabilities from Model C ASM conditional failing probabilities and from linearized RSD pollutant passing probabilities.

2.5 Selection of Vehicle Descriptions to Model

The failure probability models to be developed in this study needed to be built on datasets that contained many observations of ASM test results for vehicles with similar combinations of model year, manufacturer, make, model, vehicle type, engine, and emission control system. We needed to determine the list of vehicle descriptions to be modeled with a goal of producing a relatively small list of vehicle descriptions with each vehicle description dataset having a large number of observations. This would reduce the number of Fprob models that would need to be built. Of course, we wanted each description to be defined by attributes that are closely associated with the different vehicle attributes that distinguish different levels of failure probabilities among different vehicle descriptions. For example, one version of traditional Fprobs used model year, make, model, engine, and emission control system to categorize vehicles for Fprob calculation and look-up. For this study, we chose to categorize vehicle descriptions differently:

- **Metering_ECS** – This descriptor is made up of a four-letter concatenation of fuel metering and emission control system and describes the major engine technologies that affect emissions. The first letter of the concatenation describes fuel metering as either fuel-injected or carbureted. If the VIN Decoder[9] result for induction was FI, SFI, EFI, CPI, CFI, DFI, MFI, MPI, or TBI, then the first letter was F for fuel-injected. If the VIN Decoder induction output was 1 bbl, 2 bbl, 3 bbl, or 4 bbl, then the first letter was C for carbureted. The second, third, and fourth letters of the descriptor were based on the VIN Decoder output for three major emission control systems used on gasoline engines. If air injection was

[9] For this study, the VIN decoding was performed using the ERG VIN Decoder version 2002.01.

used, then the second letter was A; otherwise it was N for none. If the exhaust system had an oxy-catalyst, the third letter was O; if it had a three-way catalyst, the third letter was T; otherwise it was N for none. If exhaust gas recirculation was used, the fourth letter was E; otherwise it was N for none. As an example, a vehicle that decoded with fuel metering as 2 bbl with air injection, an oxy-catalyst, and exhaust gas recirculation would have a Metering_ECS code of CAOE.

- **Engine** – The descriptor for engine was made up of a concatenation of the VIN Decoder outputs for displacement, displacement units, cylinder configuration, and aspiration. The displacement and its units were used as they are output from the VIN Decoder, that is, displacement in liters rounded to the nearest 0.1 liter with a unit of L or displacement in cubic inches rounded to the nearest cubic inch with a unit of CI. Cylinder configurations describe the orientation and number of cylinders in the engine. Aspiration is either natural, turbo-charged, or super-charged which were designated as _N, _T, and _S. For example, a naturally aspirated 5.7L V8 engine would have an engine descriptor of 5.7L_V8_N.

- **Make_CarTrk** – This descriptor is a concatenation of VIN Decoder make and vehicle type. For the make, we just used the VIN Decoder output value. For the CarTrk part of the descriptor, if the VIN Decoder output for vehicle type was CAR, then CarTrk was designated as CAR. If the VIN Decoder output for vehicle type was TRK, BUS, MPV, VAN, or INC, then CarTrk was designated as TRK. For example, a Ford Taurus would be designated as FORD_CAR.

For this study, we defined vehicle description as the combination of Metering_ECS, Engine, and Make_CarTrk. Defining vehicle description with these three descriptors makes distinctions among makes, cars versus non-cars within a make, engines within Make_CarTrk, and different types of metering and emission control system technology for different engines of the same description. The reader will note that model and model year are not part of the vehicle description. By not including model in the vehicle description, we have assumed that engines with their fuel metering and emission control systems for the same make and vehicle type have similar ASM failure probability characteristics regardless of the model that the engine is in. We believe that this is a reasonable simplification of vehicle description that will produce only a small error in the failure probabilities that are calculated. We decided not to use model year as part of the vehicle description since each manufacturer tends use a given engine with a constant fuel metering and emission control system for a number of model years. We assumed that the gross failure probability characteristics over those model years will be relatively constant because of this. Nevertheless, when we built models we included model year as one of the independent variables so that any improvements in the fuel metering or emission control systems that were used during a model year range could be reflected in the estimated ASM failure probabilities.

ASM failure probabilities were calculated for each vehicle description where the data was sufficiently abundant to create the model. To select vehicle descriptions for modeling, we decoded all VINs present in the California VID from June 1998 to March 2005. We retained all unique VINs that decoded without any error messages and categorized them by Metering_ECS as described above. This binning produced the 35 Metering_ECS categories with the frequencies shown in Table 2-2. The table shows that the four largest Metering_ECS combinations for carbureted vehicles included 89.1% of all carbureted vehicles in the VID. The top four Metering_ECS combinations for fuel-injected vehicles included 98.7% of all fuel-injected vehicles in the VID and, together, these eight combinations included 97.2% of the vehicles in the VID. The four selected carbureted categories all have exhaust gas recirculation with all four combinations of air injection and either oxy-catalyst or three-way catalyst. The four fuel-injected categories all have three-way catalysts with all four combinations of air injection and exhaust gas recirculation.

In the first filtering step, we selected only vehicles with the eight Metering_ECS descriptors in the boxes in Table 2-2 for further consideration in building ASM failure probability models. The advantage of choosing just the eight Metering_ECS categories is that the number of ASM failure probability models that are required is substantially reduced while still covering 97.2% of the vehicles in the I/M program fleet. This selection eliminates many Metering_ECS combinations from further consideration. Engines with unusual fuel metering systems (Metering = X in Table 2-2) such as CNG, flexible-fueled vehicles, electric vehicles, and LPG vehicles are eliminated. Vehicles with neither oxy-catalysts nor three-way catalysts are also eliminated. These non-catalyst vehicles dominate the pre-1975 vehicle fleet. Their elimination essentially removes the 1974 model year vehicles from further consideration in this study. Other combinations of the descriptors that make up the Metering_ECS variable are also eliminated.

The second filtering step was to keep only those combinations of Make_CarTrk that dominate each of the eight Metering_ECS categories. We did this by arbitrarily eliminating Make_CarTrk categories where the number of observations was less than the square root of the total number of observations in the Metering_ECS category.

In the third filtering step, we examined the number of observations for different engines within each of the Make_CarTrk categories. We eliminated engine categories where the number of observations was less than the square root of the total number of observations in the Make_CarTrk category.

Table 2-2. Frequency Distribution of Metering_ECS Categories

Metering_ECS	Number of VINs	Metering-Cumulative VINs (%)
CATE	1,645,263	52.8%
CAOE	678,205	74.6%
CNOE	244,939	82.5%
CNTE	208,380	89.1%
CANE	103,991	92.5%
CAON	66,682	94.6%
CNNN	57,849	96.5%
CNNE	54,367	98.2%
CANN	37,537	99.4%
CATN	17,705	100.0%
CNON	63	100.0%
CNTN	6	100.0%
FNTE	11,323,920	56.1%
FATE	4,076,194	76.3%
FNTN	3,966,772	96.0%
FATN	551,614	98.7%
FNOE	106,459	99.2%
FAOE	92,736	99.7%
FNNE	25,951	99.8%
FANN	19,456	99.9%
FNON	9,555	100.0%
FANE	5,104	100.0%
FAON	663	100.0%
FNTX	441	100.0%
FNNN	196	100.0%
XNTE	24,804	
XNNN	21,533	
XNNE	9,683	
XATE	6,584	
XATN	1,786	
XNXN	954	
XXTX	560	
XNOE	43	
XNON	30	
XNTN	30	

In the fourth level of filtering, the same approach was applied to Model Years for each Engine category.

Performing this filtering helped reduce the number of ASM failure probability models to be built while maintaining the ability to predict ASM failure probabilities on almost all of the vehicles in the I/M program. After the four filters for Metering_ECS, Make_CarTrk, Engine, and Model Year had been applied to the entire dataset of unique VINs without decoding errors, we found that 96.9% of the unique, properly-decoding VINs had been retained.

Once the filtering was complete, the SAS program[10] created two datasets. The first dataset[11] was a list of the VINs of all of the vehicles that had survived all of the filtering. The historical VIN inspection records for only these VINs were used to create the datasets on which the Fprob models were built. The second dataset contained the surviving combinations[12] of Metering_ECS, Make_CarTrk, Engine, and Model Year, to serve as a look-up table so that the Fprobs of new VINs can be calculated during application of the Fprob models. The surviving combinations of vehicle description and model year with the counts of number of unique VINs are given in Appendix J.

2.6 ASM Mode/Pollutant Pprobs for VID History Inputs

The California VID has been collecting inspection information on vehicles tested in the I/M program since June 1998, when the ASM test was adopted in enhanced areas, and before that date for the two-speed-idle test. The millions of inspections in the historical VID represent a largely unused source of information for how vehicles interact with the I/M program. In this study, we want to use the historical VID information to help make improvements in predicting vehicle ASM failure probabilities. This subsection describes the approach taken in this study to analyze the VID information and develop models to provide improvements to the traditional ASM failure probabilities.

Early in the project, we investigated the relative importance of ASM cutpoints, vehicle age, previous-cycle initial-test I/M result, and time since previous cycle on ASM failure probability for individual ASM mode/pollutant tests for Ford Tauruses with the 3.0 liter V6 engine (Metering_ECS = FNTE, Make_CarTrk = Ford_Car, Engine = 3.0L_V6_N, and Year = 1986 to 2002). During those early analyses, we saw trends for failure probability of the Taurus as a function of the different VID history attributes; however, we were never able to arrive at functionalities of VID history variables that described failure probability <u>perfectly</u>. One of the reasons for this was the large number of observations for Ford Taurus in the VID. Because of the large number of observations, any lack-of-fit test was statistically significant. While the lack of fit was statistically significant, it was possible that it was not practically important to the

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[10] The name of the program that performed all of the filtering and produced the two datasets was /bigrig/DecisionModel/ASMFprob2005/FindVehCats.sas
[11] The SAS dataset containing the VINs of all vehicles surviving the filtering was /bigrig/DecisionModel/ASMFprob2005/pass4vinscats.sas7bdat
[12] The name of the dataset containing all of the surviving combinations of vehicle descriptions was /bigrig/DecisionModel/ASMFprob2005/pass4cats.sas7bdat

estimation of ASM failure probabilities. We realized that what we needed was not a perfect fit of failure tendencies but, rather, simply a significant improvement over traditional Fprobs. When we considered the problem from this point of view, the approach became clear. The goal was to find transformations of VID history variables that would produce a substantial improvement in the accuracy of ASM passing probabilities over traditional Fprobs.

The modeling of ASM mode/pollutant passing probabilities as used in Equations C-14 through C-22 is key to using the abundant data in the VID to improve the overall ASM failure probabilities. Those nine equations are used not only to predict overall ASM failure probabilities in Model C, but also overall ASM failure probabilities in Model B, which represents an update of traditional overall failure probabilities, and in Model D which provides overall ASM failure probabilities based on VID history as well as RSD measurements. Accordingly, the models developed for Equations C-14 through C-22 are at the core of answering the questions in this RSD pilot study.

As mentioned earlier, we found that logistic regression was able to take advantage of ASM pass/fail results to build models for ASM mode/pollutant probabilities for each vehicle description, which is defined by Metering_ECS, Make_CarTrk, and Engine. The functional form for predicting passing probabilities, Pprob, is given by:

$$\text{Pprob} = \exp(\text{arg}) / (1 + \exp(\text{arg})) \qquad \text{[Equation 2-1]}$$

where the argument, arg, is a function of VID history variables. For traditional Fprobs:

$$\text{arg} = \text{arg}^\circ \qquad \text{[Equation 2-2]}$$

where: ° denotes the model-year average.

The "trick" that we used to bring VID history information into the passing probability models was to use a Taylor expansion of the argument around the mean values of the VID history variables of each model year in the model:

$$\begin{aligned} \text{arg} = {} & \text{arg}^\circ \qquad \text{[Equation 2-3]} \\ & + \frac{\partial \text{arg}}{\partial \text{t\_Age}}(\text{t\_Age} - \text{t}^\circ\text{\_Age}) \\ & + \frac{\partial \text{arg}}{\partial \text{t\_CtPt}}(\text{t\_CtPt} - \text{t}^\circ\text{\_CtPt}) \end{aligned}$$

$$+ \frac{\partial \arg}{\partial t\_PrevInitPass}(t\_PrevInitPass - t°\_PrevInitPass)$$

$$+ \frac{\partial \arg}{\partial t\_TSPrev}(t\_TSPrev - t°\_TSPrev)$$

$$+ \text{higher order terms}$$

where ° denotes the model-year average of the variable
t_Age is the transformed vehicle age (years)
t_CtPt is the transformed ASM mode/pollutant cutpoint (ppm for HC and NX, % for CO)
t_PrevInitPass is the transformed previous-cycle initial-test ASM result (1 = Pass, 0 = Fail)
t_TSPrev is the transformed time since previous cycle (days)

In the Taylor expansion in Equation 2-3, the intercept value, arg°, for each model year represents the zeroth order estimate of the argument, and the Taylor expansion terms are first order corrections for the VID history attributes. Use of just the zeroth order term would produce Pprobs equivalent to one minus the traditional Fprobs. One of the advantages of expressing the argument in terms of a Taylor expansion is that in the event that one or more of the VID history variables is not available, the term containing that variable can simply be dropped from the argument. In this case, the estimated passing probability produced by the model will not be as good, but it will still be a reasonable estimate of the passing probability since the model year value and other VID history inputs will still influence the estimated passing probability value.

It is important to understand that the calculation of the argument by the Taylor expansion will not be, nor is it intended to be, a perfect fit of the ASM test results in the VID. It is intended to be a major improvement to more accurately estimate overall ASM failure probabilities beyond those of the traditional ASM Fprobs. It can be expected that in the future it may be desirable to add additional higher-order terms to the Taylor expansion to make the estimation of overall Fprobs even more accurate.

Based on an analysis of the data trends, which are described below, the transformations for the different VID history variables will be chosen in an effort to linearize the argument as a function of the transformed VID history variables.

Timeframe – The use of time in the development and application of the models in this study is important to understand. During model development, we take advantage of the chronological history of the events that affect an individual vehicle's overall ASM failure status and emissions. There are three distinct sets of events that we will consider: the previous cycle, the decision point, and the next cycle.

The decision point is the point in time when I/M program staff decide whether an individual vehicle should continue in the Normal I/M Process or be exempted, directed, called-in, or scrapped. The date of the decision point for an individual vehicle can be determined by different events. For example, Directing and Exempting decisions could be made a few weeks before the vehicle is expected to return for its biennial inspection; in this case the decision point is triggered by the biennial anniversary date. For Calling-In and Scrapping, decisions could be made mid-cycle triggered by recent elevated RSD measurements on individual vehicles. Alternatively, Calling-In and Scrapping consideration could be made at any time based on consideration of a periodic small random subset of the I/M fleet. The decision point date should always occur after the previous cycle has been completed and before the next cycle begins. The decision point should never occur while a vehicle is undergoing a series of inspections and repairs to avoid interfering with the Normal I/M Process.

The previous cycle, if one exists, for an individual vehicle will typically be made up of a series of inspections at different date-times. The inspections may be ASM inspections or two-speed-idle inspections. The first inspection of this cycle is defined as the initial test which is defined as the first test following a previous certification. It is important to identify the initial test even if the reason for the test is given as "pre-test." It is the results of the initial test of the previous cycle that are used in the ASM failure probability models.

The other feature of the previous cycle that is important to model building and application is identification of the repair date. Because the VID does not contain a specific date that repairs were made in a given cycle, we estimated the repair date as the date of the ASM test that was the first passing test following a previous fail. Again, we allowed a variety of inspection reasons for that passing test when determining the repair date. The SAS code that makes these determinations is relatively complex.

The next cycle follows the decision point. The only result that we are concerned with in the next cycle is that of the initial ASM test. The same rules as were used for determining the initial test of the previous cycle are used for determining the initial test of the next cycle. In this document, we will frequently refer to the initial ASM test of the next cycle as the AFD, which stands for ASM following decision point.

The other event that is important is the measurement by RSD, if it exists. For model development, the RSD will always occur after the completion of the previous cycle and before the beginning of the next cycle. The RSD can occur before or after the decision point.

For model development, the variable being modeled is the pass or fail result of the AFD. Models that use VID history will use variables obtained from the previous cycle to create inputs. This will include the previous-cycle initial-test pass/fail result and the time since previous cycle. The time since previous cycle is the time difference in days between the previous-cycle initial-test and the AFD if the previous-cycle initial-test result was a pass and is the difference between the previous-cycle repair date and the AFD if the previous-cycle initial-test result was a fail. The ASM mode/pollutant cutpoints that are used in the models are for the cutpoints of the AFD since that is the response variable. The age of the vehicle is for the vehicle age at the time of the AFD.

If RSD measurements are available and are to be used in one of the models, then the RSD must occur before the AFD and after the previous cycle has been completed. The length of time between the date of the RSD measurement and the AFD would be expected to have an influence on the relevance of the RSD measurements to the AFD pass/fail result. We would expect that, as the RSD measurements became old, they would become stale and have less influence on the pass/fail result. However, our analysis indicates that the RSD measurements seem to maintain the same degree of relevance even when they become 12-months old.

For application of the probability models, VID history information from the previous cycle and/or RSD measurements are available; however the results of the AFD are not available since they are in the future. Instead, the AFD results are predicted by the model. Of course, to make those predictions, the model requires inputs for the ASM mode/pollutant cutpoints at the time of a hypothetical AFD and the time since the previous cycle to the hypothetical AFD.

Model Year – Rather than use a function for the effect of model year, the models were built using model year as a class or categorical variable. In Equation 2-3, arg° has different constant values that correspond to each of the model years for a given vehicle description. How these constants vary with model year is simply determined by the regression. When the transformed variables for all subsequent terms in the equation are at the average value for the model year, all of the subsequent terms become zero. In this situation, the Pprob calculated by Equation 2-3 for that particular vehicle description and a particular model year simply becomes the Pprob for the average vehicle with that description and model year which is analogous to the traditional Pprob value.

In general, we have observed that the model year intercept values calculated by the regression are monotonically increasing with respect to model year for a given vehicle description. This can be seen in the model year regression coefficients shown in Table C-7 for the ASM 2525 NX unconditional model for FNTE, Ford_Car, 3.0L_V6_N. The upward trend of these model year values reveals the general trend for increasing passing probabilities of Ford Taurus with more recent model years when all other variables in the regression are at the average values for each of the models. For example, the average age of the 1986 Fords used in the regression are much older than the average age of the 2001 Fords used in the regression. Accordingly, since the model year values are not calculated at constant age, they reflect the effect of age as well as any minor technology changes that occurred as new model year vehicles were developed.

Vehicle Age – In Equation 2-3, the second term involves a correction in the argument for the effects of vehicle age. This correction is to be made to the model year intercept value, represented by arg°, based on how much different the age of the vehicle in question is from the average age of the dataset used to calculate the model year intercept value. In the equation, ∂arg/∂t_Age represents the regression coefficient for the difference between the transformed age and the model-year-average transformed age. Other than determining the regression coefficient for age, the larger question is what transformation should be made to age such that the difference between the transformed age and the model-year-average transformed age is relatively linear with the argument.

Our analysis of the Ford Taurus data indicated that a reasonable transformation was ln(ln(Age)). We found that this transformation reasonably mimicked the relative effects of age on passing probabilities for new versus old cars. The data indicated, when fail rates were considered in logit space, that vehicle aging occurs most rapidly in new vehicles. This makes some sense. For example, a one-year-old vehicle is much more different than a brand new vehicle in comparison with the difference between a 25-year-old vehicle and a 24-year-old vehicle. For the new vehicle, one year of aging is the difference between a new vehicle and a used vehicle while for a 24-year-old vehicle, one year of aging is inconsequential; the old vehicle is still an old vehicle.

ASM Mode/Pollutant Cutpoint – The dependence of ASM passing probabilities upon ASM mode/pollutant cutpoints is one of the most important functionalities that has been left out of traditional ASM Fprobs. The general dependence of the passing probability on the cutpoint is clear; as the cutpoint is lowered, the probability of passing the ASM mode/pollutant increases.

But what transformation of the cutpoints should be used in the third term of Equation 2-3, and what data can be used to validate the transformation and determine the coefficient ∂arg/∂t_CtPt?

For any vehicle description, most observations in the VID will contain only one or two different cutpoint values. In general, such a dataset will not be sufficiently diverse to generate a model that can be used to estimate ASM mode/pollutant passing probabilities for any mode/pollutant cutpoint. The "trick" that we used to enhance the dataset was to replicate the dataset four times and apply four artificial cutpoints, which were larger than the original cutpoint used during the ASM test, to determine the pass/fail "result" of each observation at each of the artificial cutpoints. The effect of the changing cutpoint is contained in the pass/fail results of the replicated observations. Artificial cutpoints lower than the original cutpoint cannot be used because the concentration measurements reported in the VID would almost always be fast-pass results, which we know to be biased. However, all inspection results with concentrations higher than the original cutpoint must be full duration ASM tests and, therefore, are not biased. This dataset replication based on higher cutpoints, therefore, produces a dataset that is five times larger than the original dataset.

While the dataset now contained at least five different cutpoints, the values of these artificial cutpoints were usually large compared to the emissions concentrations of the bulk of the inspected fleet. Accordingly, the specific cutpoint functionality on passing probabilities is not clearly determined. For guidance, we considered the limits that the cutpoint functionality should have at both ends of the cutpoint range. As the ASM mode/pollutant cutpoint approaches zero, the ASM mode/pollutant passing probability should approach zero; as the ASM mode/pollutant cutpoint approaches infinity, the ASM mode/pollutant passing probability should approach one. We also know that the distribution of ASM mode/pollutant emissions, which is described by the passing probability versus emissions concentration curve, should be positively skewed. Given these expected trends in the effect of ASM mode/pollutant cutpoint on ASM mode/pollutant passing probability, we chose the transformation of cutpoint to be ln(CtPt). The passing probability models that were built on the dataset using this transformation provided good fits to the observed ASM mode/pollutant pass/fail results. The natural log transformation of ASM mode/pollutant concentrations is likely to be not exactly correct. However, it describes the observed results well and it has boundary conditions that make sense. It meets the needs of the third term in Equation 2-3 to make a substantial improvement in the estimated passing probabilities beyond those for traditional Fprobs.

By describing the passing probabilities throughout the entire range of ASM mode/pollutant concentrations, based on using ASM inspection results from vehicles that have failed the inspection, we are inherently assuming that the distribution of vehicles that pass the ASM inspection are sampled from the same distribution as those that failed the ASM inspection. In other words, we are assuming that the emissions distribution of vehicles of the same description is smooth across the concentrations where the cutpoints are located. Given that there are many possible functions that could describe the passing probability distribution, it is desirable to confirm that the ASM mode/pollutants for a given vehicle description for vehicles that failed the inspection and that passed the inspection come from the same distribution and that the log transformation of the emissions concentration describes that distribution. To be able to do this confirmation requires a dataset where all of the ASM mode/pollutant inspections are for full-duration tests. We know that there is a large set of full-duration ASMs from a portion of the 2002 California inspection season that could be used to confirm or discover the proper functionality. However, that confirmation effort must be performed in a subsequent effort.

Previous-Cycle Initial-Test Pass/Fail Result – From other research, it is known that vehicles that initially failed one I/M cycle are more likely to initially fail a subsequent cycle than vehicles that initially pass the first I/M cycle. For the development of ASM mode/pollutant passing probability models, we wanted to be able to include this functionality so that a history of passing or failing can be reflected in forecasted probabilities.

In this instance, there is no transformation to determine. There are only a few possibilities for the previous-cycle initial-test result. If the previous-cycle initial-test was an ASM, it was either a pass or a fail. If the previous-cycle initial-test was a two-speed-idle test, then for modeling purposes in this study, we chose not to use the pass or fail result of the two-speed idle test since we expect that a previous-cycle two-speed-idle result and the next-cycle initial-test ASM result would not be well-correlated. In addition, two-speed-idle tests have four mode/pollutant components while ASM tests have six mode/pollutant components. The modes do not correspond and two-speed-idle tests do not produce NX emission test results. The other possibility is that there was no previous-cycle test of any kind. In this situation, the vehicle is new to the I/M program either because it is a relatively new vehicle or it entered the I/M fleet from outside the I/M area.

Therefore, to handle the fourth term in Equation 2-3, we created two indicator variables:

- **prevint_asm_exist** – Has a value of one if the previous-cycle initial-test was an ASM. Otherwise the value is zero.
- **prevint_tsi_exist** – Has a value of one if the previous-cycle initial-test was a two-speed idle. Otherwise it is zero.

Time Since Previous Cycle – We expect and our data analysis shows that after a vehicle fails its previous-cycle initial-test ASM mode/pollutant inspection, and is repaired and ultimately certified, the failing probability of the vehicle increases over the following months. This is shown in Figure 2-1 for 1986 to 2002 Ford Tauruses with the 3.0L engine. (For now, consider only the data points in the figure, and ignore the trend lines.) Approximately 70,000 VID observations were used for this figure. The ASM results in Figure 2-1 from 2 months until about 22 months after the previous cycle are the result of change of ownership inspections. The ASM results that are for 26 months and greater are from inspections of owners who were late in having their vehicles inspected. About half of the 70,000 observations are clustered between 22 and 26 months after the previous-cycle inspection.[13]

The figure shows that in the first four months or so, for the vehicles that failed the previous-cycle initial-test, the fraction of vehicles that failed the next ASM rose rapidly to about 18% and then rose to about 30% at 24 months after the previous cycle. For those vehicles that passed the previous-cycle initial-test ASM inspection, which are shown by the smaller green dots, a similar but less dramatic trend is seen. This plot demonstrates that previously failing vehicles subsequently fail at a higher rate than previously passing vehicles do, and that the fail rate of previously failing vehicles increases faster in the long period between cycles than the fail rate of previously passing vehicles does.

If we use the same data that created Figure 2-1 and take the logit of the failure fraction, Figure 2-2 is produced. Taking the logit effectively moves the data from probability space into logit space, the space in which Equation 2-3 applies. Figure 2-2 shows that the next-cycle ASM behavior for the vehicles that previously failed and the vehicles that previously passed seem to be on nearly parallel curves. Both of the curves are made of two similar parts: a rapid rise in the first several months after the previous inspection followed by a relatively linear time trend after about four months. For demonstration purposes, we have drawn parallel straight lines with identical slopes through the linear portion of both sets of data points in Figure 2-2. When these straight, parallel lines are taken back into probability space, they produce the curved lines in Figure 2-1. Figure 2-1 shows that the lines pass through the points in both sets of data, and the slopes of the trends are substantially different just as the trends of the data points are.

[13] In using VID inspections from change-of-ownership inspections (2 to 22 months), regular on-schedule biennial inspections (22 to 26 months), and late inspections (>26 months) together to build Fprob models, we are assuming that the pre-inspection-repair behaviors of these three catergories of inspections – and therefore their ASM Fprobs – follow the same trend. There are reasons to believe that the pre-inspection-repair behaviors and Fprobs of these categories might be different.

Figure 2-1. Overall Failure Probabilities Following Previous-Cycle ASMs (FNTE Ford_Car 3.0L_V6_N 1986-2002)

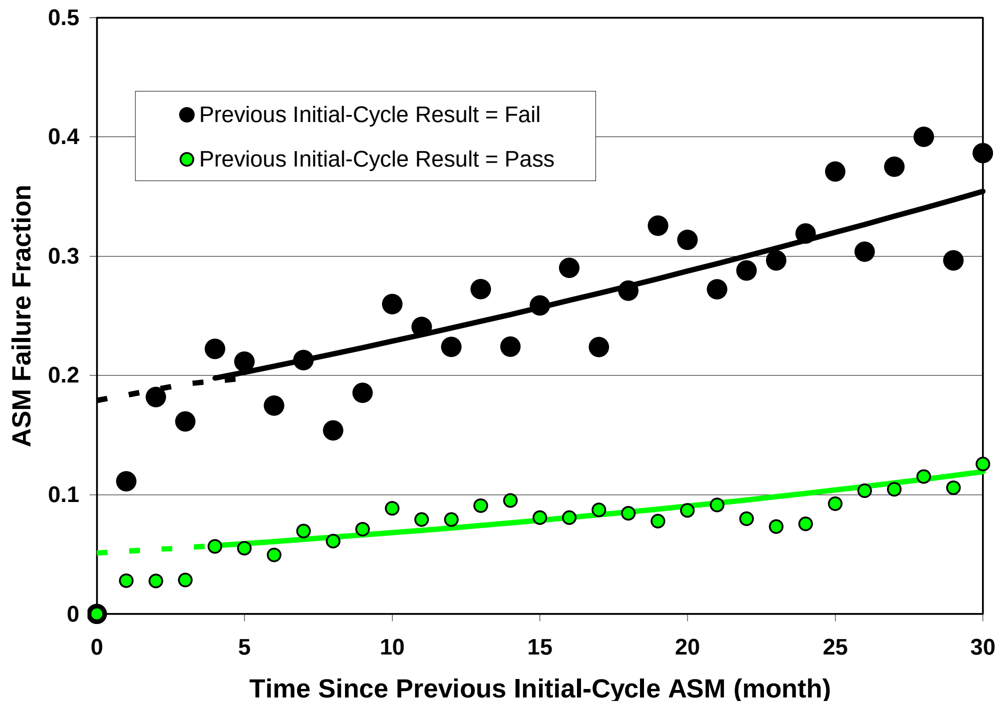
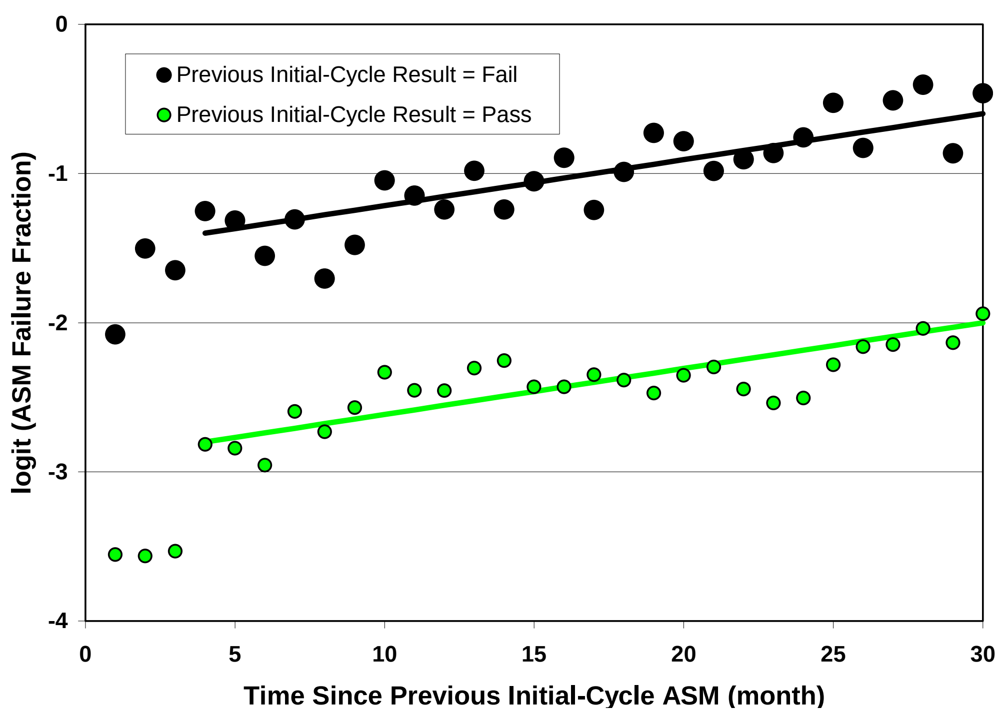


Figure 2-2. Logit of Overall Failure Probabilities Following Previous-Cycle ASMs (FNTE Ford_Car 3.0L_V6_N 1986-2002)



In this study, we did not attempt to model the rapid rise in the logit of the failure probability during the first three months after the previous cycle. Part of the reason for ignoring the rapid rise in ASM failure probability during the first three months is that there are very few ASM tests in the VID that can support development of a coefficient to predict this effect for each vehicle description.

Based on data examinations such as these, we believe that in logit space the effect of the previous-cycle initial-test result is relatively independent of, and therefore separable from, the effect of time since previous cycle. Accordingly, we modeled the logit of the failure probability's previous-cycle initial-ASM dependence as made up of two parts: a time-independent term (the term in Equation 2-3 using t_PrevInitPass) that depends only on whether the previous-cycle initial-ASM was a pass or fail, and a time-dependent term (the term in Equation 2-3 using t_TSPrev) that is linear with the time since the previous-cycle initial-ASM inspection using only data from Month 4 and later.

Logistic Regression Model Statement – After taking all of the previous discussion into account, we present the argument model statement to be used for the logistic regressions for the Model C ASM mode/pollutant passing probability models:

arg = arg° [Equation 2-4]

+ A • (lnlnAge - lnln°Age)

+ B • (lnCtPt - ln°CtPt)

+ C • (PrevInit_Pass – PrevInit_Pass°) • PrevInit_ASM_Exist

+ D • (DSP_ASM – DSP_ASM°) • PrevInit_ASM_Exist • **TSP > 90d**

+ E • (PrevInit_ASM_Exist – PrevInit_ASM_Exist°)

+ F • (1- TSP>90d) • PrevInit_ASM_Exist

+ G • (PrevInit_TSI_Exist – PrevInit_TSI_Exist°)

+ H • (DSP_TSI – DSP_TSI°) • PrevInit_TSI_Exist • **TSP > 90d**

+ I • (1-TSP> 90 d) • PrevInit_TSI_Exist

where:

lnlnAge	=	The natural log of the natural log of the vehicle age in years at the time of the AFD using January 1st of the vehicle model year as the birthdate of the vehicle.
lnCtPt	=	The natural log of the ASM mode/pollutant cutpoint for the AFD with units of ppm for HC and NX and % for CO
PrevInit_Pass	=	The previous-cycle initial-test ASM mode/pollutant result (Pass = 1, Fail = 0)
PrevInit_ASM_Exist	=	An indicator variable for the previous-cycle initial test. 1 if the previous cycle initial test is an ASM. 0 if it is not an ASM.
Previnit_TSI_Exist	=	An indicator variable for the previous-cycle initial test. 1 if the previous cycle initial test is a TSI. 0 if it is not a TSI.
DSP_ASM	=	the number of days between the previous-cycle initial-ASM test and the AFD if the result of the previous-cycle initial-ASM test is a pass. If the previous-cycle initial-ASM test is a fail, then the number of days between the previous-cycle repair date and the AFD.
DSP_TSI	=	The number of days between the previous-cycle initial-two-speed-idle test and the AFD if the previous-cycle initial-test was a two-speed-idle test.
TSP>90d	=	An indicator variable that tells if the number of days between the previous-cycle date and the AFD date is greater then 90 days or not. It has a value of 0 if it is not greater than 90 days and a 1 if it is greater than 90 days.
°	=	Denotes that these variables are the model-year average for this vehicle description

When the logistic regression models are built for each vehicle description, arg° and the coefficients A through I shown in Equation 2-4 are determined. The indicator variable TSP>90d is provided in the regression so that all observations can be used to determine all coefficients. However, because we have not modeled the non-linear time dependence of the first 90 days after the previous-cycle inspection explicitly, the F- term and I- term "absorb" the variability in the data that was present for observations where the AFD occurred 90 days or less after the previous-cycle date. When the models are used to predict the ASM mode/pollutant passing probabilities, the terms and factors that are bold in Equation 2-4 must be dropped. This produces passing probabilities for the first three months after the previous-cycle ASM test that are extrapolated from the data where the time since the previous-cycle is greater than 4 months.

Sparse Data Contingency – Under some modeling situations for vehicle descriptions and/or ASM passing probability conditional models, small datasets and/or a small number of failing observations have been observed to prevent the SAS logistic regression algorithm from converging. The SAS logistic regression output reveals when non-convergence occurs. In these situations, we took an alternative approach to create a larger dataset so that convergence would occur and coefficients would be determined in these sparse data instances.

The normal situation is to build separate models for each combination of Metering_ECS, Make_CarTrk, and Engine with different model years as the intercept class variable (arg°). When we ran into the non-convergence problem, we combined data such that the dataset observations all had the same Metering_ECS and Make_CarTrk values and the model statement contained class variables for Engine as well as class variables for Year. In most cases, this allowed the models to converge. The resulting coefficients chosen for the final models were from the models made at the Engine level if they converged and from the models built at the Make_CarTrk level if the models built at the Engine level did not converge. For those few instances when models still would not converge when built at the Make_CarTrk level, no models were provided for use in any application.

A description of the preparation of the modeling data is given in Appendix K.

2.7 ASM Pollutant Pprobs for RSD Inputs

For the development of models that use remote sensing measurements to predict ASM failure probabilities, we decided to use RSD measured concentration readings. We chose RSD concentrations rather than RSD gram per gallon readings because RSD concentrations have the same units as ASM measurements and cutpoints, which are used to determine whether a vehicle passes or fails its inspection. Using RSD concentrations also simplifies the calculations since there is no need to convert from concentrations to grams per gallon, which requires estimates of vehicle fuel economies.

In essence, we view RSD measurements as one-half-second snapshots of vehicle emissions that are similar to the 90-second snapshots of vehicle emissions provided by each of the two ASM test modes (2525 and 5015). We know from earlier analyses that the logit of the ASM mode/pollutant failure probabilities are relatively linear with the natural log of the corresponding mode/pollutant concentrations. Therefore, we expected that the logit of the ASM mode/pollutant failure probabilities would be relatively linear with the natural log of the corresponding RSD measured concentration. Our analysis of the ASM pollutant failure probabilities for inspections that followed RSD readings in the pilot dataset indicated that the logit of the failure probabilities was linear with the natural log of the RSD readings for CO and NX. In the case of RSD HC we found that the relationship could be described as segmented linear.

An appropriate transformation for measured RSD readings was needed to make the RSD values useful in predicting ASM failure probabilities. While there was evidence that the log of the RSD readings represented the true relationship between ASM failure probability and RSD concentration, the abundance of negative RSD reported values[14] in the dataset prevented the use of the log transformation without going into the complex-number space. For these reasons, we sought an RSD transformation that would preserve any emissions information that was contained in negative RSD values and would be linear with ASM pollutant failure probabilities.

One traditional method for transforming the negative values is to first add a small positive constant to all values in the dataset and then make a transformation. The constant that is added to all RSD values needs to be relatively large compared to all the RSD values because the smallest RSD values are typically quite negative. We tried this approach and tested a wide variety of constants to be added to the RSD values. We tried small constants, as well as large constants, and followed the addition of the constant by a power transformation. These transformed RSD values were then compared with the logit of the ASM failure probabilities to determine if the relationship was linear. In no case did we find a linear relationship. In fact, the highest non-linearity was where the most abundant RSD data was located. The approach of adding a constant to the RSD values, at least when it is followed by a power transformation, produced an unacceptable transformation.

Another standard technique that can be used to transform measurements that become negative is ranking. In ranking, the RSD measurements are sorted and a relative rank, or fractile, is assigned to each observation. The fractiles are, of course, all non-negative and therefore, can be used in a wide variety of traditional transformations. The small drawback of this approach is that the dataset that is used to determine the fractiles must be retained for all future calculations so that the fractile values that correspond to new RSD values can be looked up.

[14] Negative RSD concentration readings are an actual and expected consequence of the RSD measurement method and arise from measurements made on vehicles with low tailpipe emissions. While negative RSD readings do not literally represent the emissions concentrations of the vehicles, the negative values, just as all RSD values, carry potentially useful emissions information. Forcing all negative values to have a value of zero would not only produce a loss in this emissions information, it would also irreparably introduce a bias into the RSD data.

We found that the ranking approach produced excellent results. The details of the transformations are shown in Appendix G. The development of the RSD-linearizing transformations was key to this study since they allow all RSD concentration measurements to be effectively merged with VID history data to predict ASM failure probabilities. The transformation models in Appendix G are used to transform RSD concentration values to values that are linear with the logits of ASM mode/pollutant failure probabilities. The transformations work properly on negative, as well as positive, RSD concentration values. The Appendix G RSD-linearizing transformations are used as inputs to the Model F equations (see Appendix F), which predict overall ASM failure based only on RSD measurements, to the Model E equations (see Appendix E), which predict overall ASM failure based on RSD measurements and ASM cutpoints, and to the Model D equations (see Appendix D), which predict overall ASM failure based on RSD measurements, ASM cutpoints, and VID history. For all of the models built in Appendices A through G, the models were built on 2/3 of the observations and validated on the remaining 1/3. The appendices also have measured vs. predicted plots for each model to show the goodness of fit for the validation, as well as, the fitted data.

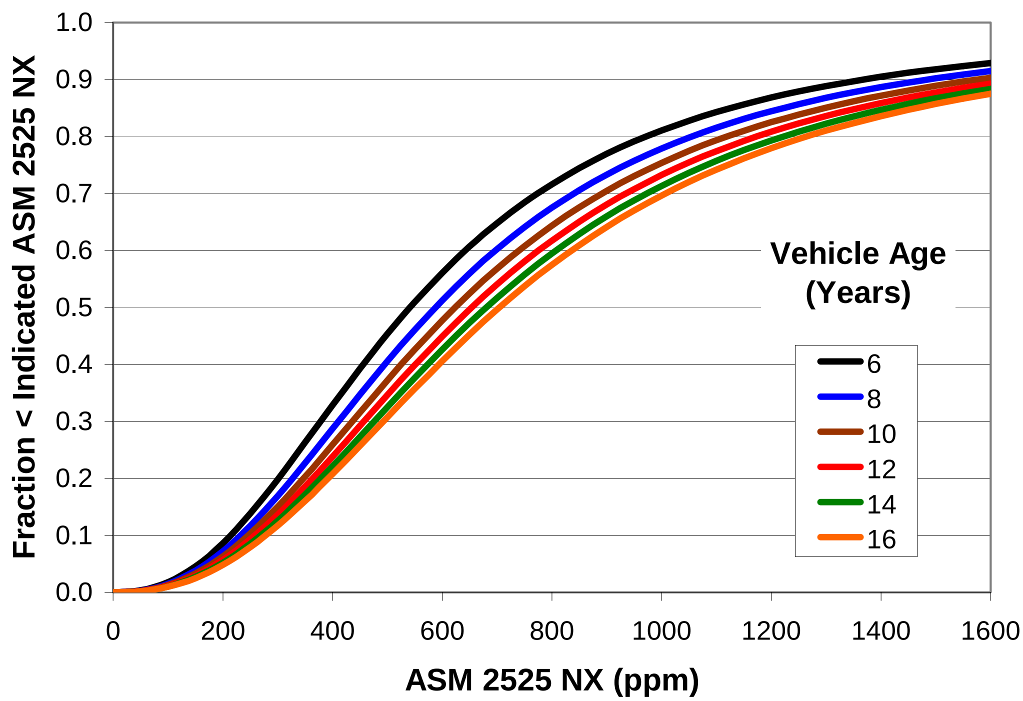
2.8 Conversion to Expected ASM Emissions and FTP Emissions

To effectively evaluate the benefits of new types of intervention in the California I/M program such as Directing, Exempting, Calling-In, and Scrapping, estimates of ASM emissions and FTP emissions are desirable. Since the benefits of intervention are accumulated over the 24 months after the decision point, the emissions benefits need to be calculated as a function of time. The models developed in this study provide ASM mode/pollutant Pprobs and overall Fprobs. In addition, we have discovered that the models that contain ASM cutpoint functionality can also be used to forecast time-dependent ASM mode/pollutant concentrations and time-dependent FTP pollutant emission rates as a function of VID history and/or RSD measurement information. This subsection describes how integration can be used to calculate these quantities.

The unconditional ASM mode/pollutant Pprobs for Models C, D, and E are given in Equations C-14, C-15, C-17, C-18, C-20, C-21, and D-8, D-9, D-10, D-11, D-12, D-13, and E-14, E-15, E-17, E-18, E-20, E-21. For any of these ASM mode/pollutant models, the Pprob can be expressed as a function of the ASM mode/pollutant cutpoint and the other variables in the model.

Figure 2-3 shows the dependence of the ASM 2525 NX passing probability (unconditional) given by Equation C-20 as a function of the ASM 2525 NX cutpoint for a specific combination of the other variables in the model: vehicle age (various as shown in the legend), previous-cycle initial-test ASM 2525 NX result = Fail, time since previous cycle = 642 days, Model Year = 1988, Metering_ECS = FNTE, Make_CarTrk = Ford_Car, Engine = 3.0L_V6_N. The plot shows that, under those conditions, the expected passing probability for a 6-year-old vehicle with an ASM 2525 NX cutpoint of 738 ppm is approximately 0.67. This means that 67% of the vehicles of the same description and under the same conditions would pass the ASM 2525 NX test. The interpretation of the plot can be restated: 67% of the vehicles of the same description under the same conditions would have ASM 2525 NX emissions less than 738 ppm. Thus, we can see that the curve in Figure 2-3 provides valuable information about the ASM 2525 NX emissions concentration for vehicles under the same conditions.

Figure 2-3. Cutpoint Dependence of ASM 2525 NX Pprob
(1988 FNTE Ford_Car 3.0L_V6_N)
(Previous-Cycle ASM 2525 NX = Fail, Time Since Previous Cycle = 642 Days)



The Pprob curve in Figure 2-3 provides a picture of the ASM 2525 NX emissions for all vehicles with the same conditions. As conditions change, for similarly-described vehicles, the curves in Figure 2-3 will “move around” with the Pprob model inputs: age, previous-cycle initial-test pass/fail result, and time since previous cycle.

However, we would like to know the best estimate of the ASM 2525 NX emissions for the vehicles under these conditions. One estimate of the vehicle emissions would be the emissions value where the probability of failing and passing are the same which occurs at a

Pprob of 0.5. We can see from Figure 2-3 that this would happen if the vehicle's emissions were about 530 ppm. This would be the median emissions of all similarly-described vehicles under the same conditions.

While we can use the curves from the Pprob model to get the median emissions, we really want the mean emissions. Can we get the mean emissions? The derivatives of the curves (∂Pprob/∂CtPt) in Figure 2-3 produce the emissions distributions shown in Figure 2-4. This figure shows ASM 2525 NX distributions for the Ford vehicle for various ages as determined from the Pprob equation. The curves also show that, as the vehicle ages, the emissions distribution moves towards higher emissions concentrations and broadens. The changes in the mean and shape of the distributions of automotive emissions with aging have been reported using remote sensing measurements[15].

We would like to know for an individual vehicle what the most likely average value for the emissions would be. The average ASM mode/pollutant concentration $\bar{x}$ can be calculated from the Pprob model by using the integral definition of mean:

$$\bar{x} = \int_0^\infty x \frac{\partial \text{Pprob}}{\partial x} dx \qquad \text{[Equation 2-5]}$$

where

Pprob = the passing probability as expressed by the ASM mode/pollutant unconditional model.

x = the ASM mode/pollutant cutpoint

The ASM mode/pollutant passing probabilities for Models C, D, and E are all of the form given by:

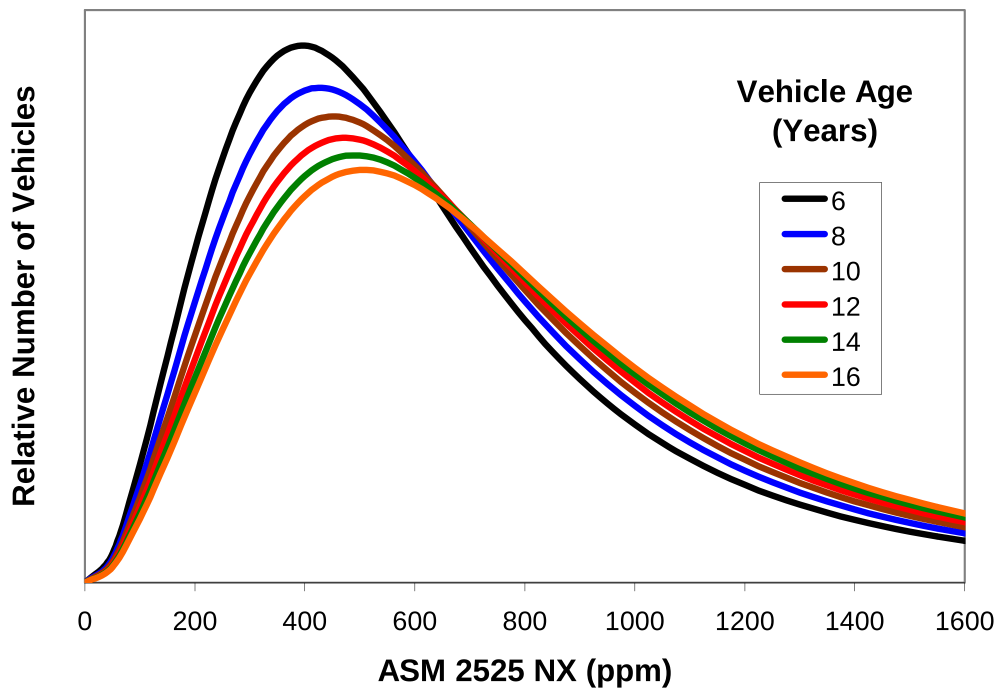
$$\text{Pprob} = \exp(\text{arg}) / (1 + \exp(\text{arg})) \qquad \text{[Equation 2-6]}$$

where

arg = A + B • ln x

[15] Yi Zhang, Gary A. Bishop, and Donald H. Stedman, "Automotive Emissions are Statistically γ-Distributed," Environmental Science and Technology, 1994, Number 28, pages 1370-1374.

Figure 2-4. ASM 2525 NX Emissions Distributions (1988 FNTE Ford_Car 3.0L_V6_N) (Previous-Cycle ASM 2525 NX = Fail, Time Since Previous Cycle = 642 Days)



The quantity A is a function of all of the VID history and/or RSD measurement terms given in the unconditional ASM mode/pollutant Pprob model equations, and A is independent of the ASM mode/pollutant cutpoint. B is the coefficient for the natural log of the ASM mode/pollutant cutpoint as given in the ASM mode/pollutant Pprob equations.

When the Pprob has the form described by Equation 2-6 and B has a value greater than 1, the integral in Equation 2-5 is given by a closed form expression in terms of A and B:

$$\bar{x} = \exp(-A/B) \bullet \text{beta}((B-1)/B, (B+1)/B) \qquad \text{[Equation 2-7]}$$

However, when B is between 0 and 1, the integral does not have a finite value. Instead of an upper integration limit of infinity for Equation 2-5, more appropriate upper integration limits (taking the ranges of observed HC, CO, and NX into account) might be 10,000 ppm for HC and NX and 20% for CO. When these upper integration limits are used, the integrated values for all positive values of B are finite, but no simple closed form expression for the integral exists. Therefore, numerical calculations of the integrations were necessary to estimate the average emissions for individual vehicles. We found that numerical integrations for the exact values of A and B could be performed in the main SAS program; however, the run time of the program became excessive. To increase computing speed, we replaced integrations in the main program with lookups of integrations using rounded values of A and B from a pre-calculated table, which was created as described below.

The first step[16] was to find the values of B and the corresponding minimum and maximum values of A for all 69,629 vehicles in the dataset and for all conditions (defined by vehicle description, model year, vehicle age, previous-cycle initial-ASM pass/fail result, time since previous cycle, pollutant/mode/condition, and Model C, D, and E) to be analyzed for Directing, Exempting, Calling-In, and Scrapping. Next, the full range of As for each given value of B was determined[9]. Next, a grid of rounded A and B values was created[17] so that integrated values would be quantized on the order of 1 ppm HC, 0.01% CO, and 1 ppm NX. To produce this for HC and NX, B values were rounded to 0.005 and A values were rounded to 0.025. To produce this for CO, B values were rounded to 0.002 and A values were rounded to 0.025. Then, the integrals for Equation 2-5 for each of the AB grid points were numerically calculated in 10,000 steps from 1 to 10,000 ppm for HC and NX and from 0.002 to 20% for CO. The results of the integration were output to a lookup table.[18]

Once we have all six ASM mode/pollutant emissions concentrations estimates from the integration, we can estimate FTP emission rates using statistical relationships developed in the past to convert ASM to FTP emissions. ERG developed comprehensive models for doing this for the Bureau of Automotive Repair in 1999[19] based on data from the Air Resources Board I/M pilot program[20] and subsequent surveillance data. In 2004, Sierra Research developed updated equations[21] using additional surveillance data and new functional forms. The Sierra functional forms, which are given in Appendix L, were used in this study to convert ASM mode/pollutant estimated concentrations to estimated FTP emission rates.

Therefore, in this study, each value of estimated FTP emissions rate in any selected month is based on a vehicle's description, age, the time since its <u>most recent</u> certification, and the pass/fail results of its <u>most recent</u> initial ASM inspection that preceded that certification. The changes in emissions that result from each inspection/repair event are not explicitly calculated.

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[16] bigrig/DecisionModel/SystemAnalysis/Core/BminmaxA.sas and BminmaxA_Step2.sas.
[17] bigrig/DecisionModel/SystemAnalysis/Core/abgrid.sas.
[18] bigrig/DecisionModel/SystemAnalysis/Core/grid_integration.lookup returns an integrated value (mean ASM concentration) when values of pollutant (HC, CO, or NX), rounded B , and rounded A are input.
[19] DeFries, Palacios, Kishan, Williamson, "Models for Estimating California Fleet FTP Emissions from ASM Measurements," BAR-991225, Eastern Research Group, Inc., December 25, 1999.
[20] "Comparison of the IM240 and ASM Tests in CARB's I&M Pilot Program," Air Resources Board, El Monte, CA, June 25, 1996.
[21] "Technical Support Document" for Evaluation of the California Enhanced Vehicle Inspection and Maintenance (Smog Check) Program, April 2004, Draft Report to the Inspection and Maintenance Review Committee, June 2004.

Instead, for the purposes of calculating failure probabilities and emissions, a new inspection cycle causes the most recent initial inspection result and certification to switch from an old event (usually about two years old) to the new event. These calculations result in values of failure probabilities and emissions that are based on the most recent and therefore newest information on the vehicle.

We know that there is a bias introduced in the estimated FTP values. This is produced by the nonlinear conversion of average ASM values to average FTP emissions values. Correction for this bias is a subject for future work.

2.9 Demonstration of Fprob Functionality

The 64 plots in Appendix M demonstrate how the functionalities used for building ASM mode/pollutant failure probability models fit the data. The data in Appendix M are for 1986 to 2002 FNTE, Ford_Car, 3.0L_V6_N vehicles. The VID data for these vehicles was fit using logistic regression and the functionalities described by Equation 2-4. The plots compare the ASM 2525 NX failure rates for binned observations in this dataset with the average of ASM 2525 NX failure probabilities predicted by Equation C-20 for the same dataset. The plots for Figures M-2, M-18, M-36, and M-51 have been reproduced in this section as Figures 2-5, 2-6, 2-7, and 2-8.

Figure 2-5 compares the fail fraction for the 1987 selected Ford vehicles as a function of vehicle age. A range of vehicle ages are available in the historical VID because vehicles of the same model year are inspected repeatedly in different calendar years. The dots in the plot show the fraction of vehicles in the dataset that fail for the different age bins. It should be noted that vehicles that are in the same age bin have a variety of differing attributes other than age. For example, the cutpoints for the ASM mode/pollutant test may be different in different calendar years or for different vehicles. The line in the plot shows the predicted average fail fractions using the model described by Equation C-20.

Figure 2-6 shows the same sort of plot for the same dataset when the dataset is binned in ranges of the ASM 2525 NX cutpoint in increments of 200 ppm. Keep in mind that the wide range of NX cutpoints in the dataset is a consequence of the replication of the dataset by artificial cutpoints at values higher than the original cutpoint. The figure shows that the model, which uses the log of the mode/pollutant cutpoint in logit space, fits the cutpoint trend quite well at concentrations greater than the original cutpoint. The model fit at concentrations below the original cutpoints is unknown since those concentrations are based on fast-pass tests.

Figure 2-5. Comparison of Observed and Modeled ASM 2525 NX Fail Rates by Age (1987 FNTE Ford_Car 3.0L_V6_N)

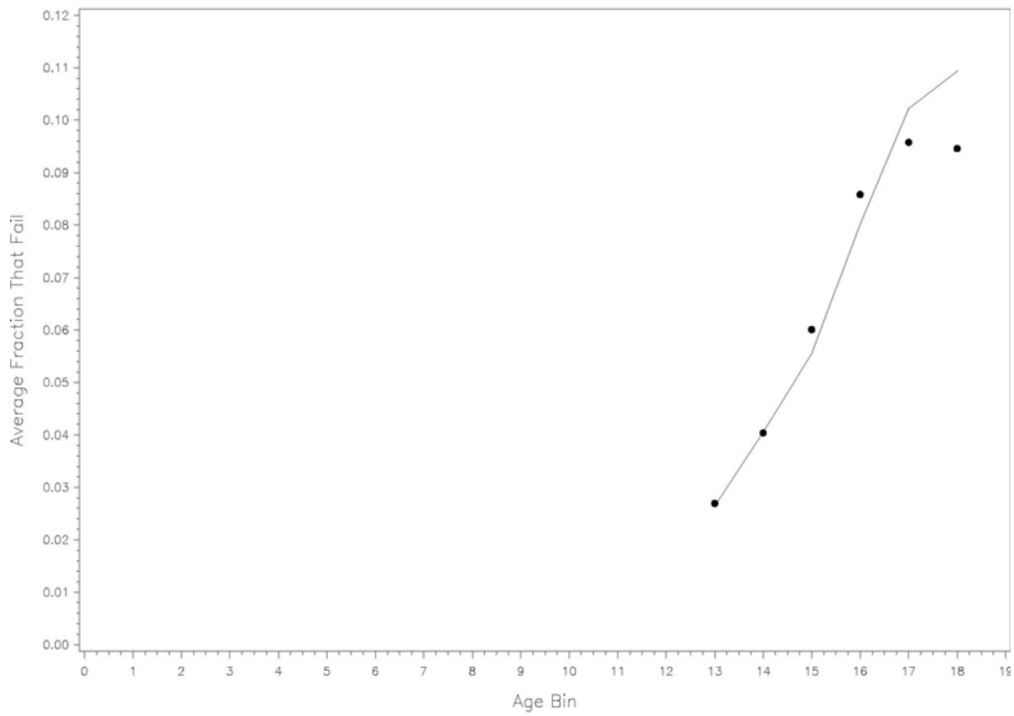


Figure 2-6. Comparison of Observed and Modeled ASM 2525 NX Fail Rates by ASM2525 NX Cutpoint (1987 FNTE Ford_Car 3.0L_V6_N)

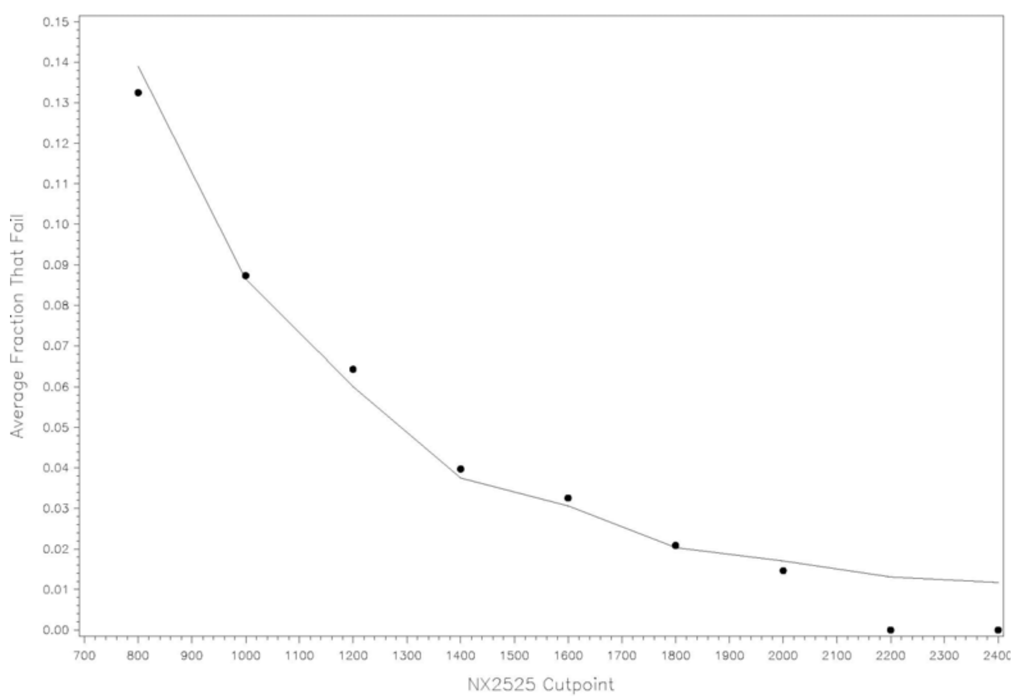


Figure 2-7. Comparison of Observed and Modeled ASM 2525 NX Fail Rates by Time Since Previous Cycle (1989 FNTE Ford_Car 3.0L_V6_N)

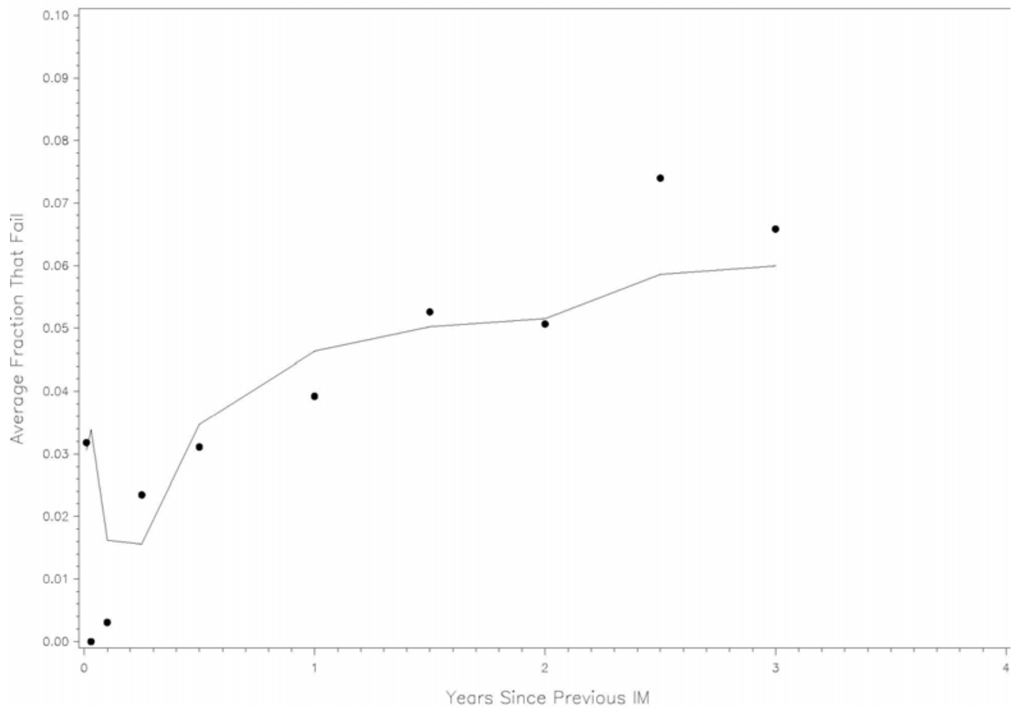


Figure 2-8. Comparison of Observed and Modeled ASM 2525 NX Fail Rates by Previous-Cycle ASM 2525 NX Result (1988 FNTE Ford_Car 3.0L_V6_N)

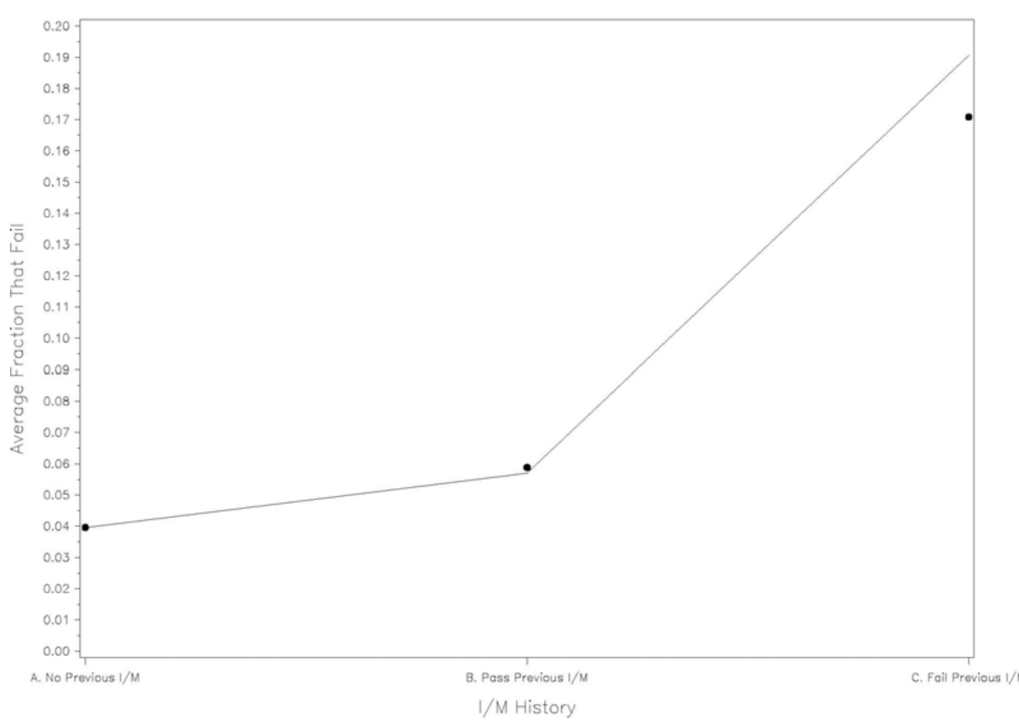


Figure 2-7 shows the trend for the 1989 selected Ford vehicles as a function of time since the previous cycle. This plot shows a rapid drop in fail fraction for the first two weeks after the previous-cycle inspection[22]. After the first two weeks, the fail fraction is near 0.00 but then rapidly rises during the next six months back to about 0.03 and then more slowly increases during the next two and a half years. This rapid decrease followed by increase in the first six months after the previous cycle is thought to be caused by the so-called "bath tub" effect.

The bath tub effect has been found to describe the initial reliability profile of some types of new products. New electronics products are a typical example. A certain fraction of new electronics will fail within the first few minutes of operation because of internal defects that were not caught during quality control. However, if a given unit survives the first few minutes of operation, it will then experience a long usable lifetime until the product fails by wearing out.

In the case of the I/M program, the repair is the product. We attempted to carefully mark the ASM results so that it was possible for us to examine the short-term reliability of repairs following initial-ASM test failures. We believe that the higher failure rate as seen at the left-most point in Figure 2-7 may be an indication of a few repairs that fail immediately. Most repairs don't fail immediately but have low failure rates as demonstrated by the second two points in the figure. Then, the period of useful lifetime for the repair comes to an end in only about four months as the failure rate returns to the 0.03 level. The effects of repair continue to degrade from that point on. It is possible that this interpretation of the trend seen in the time since previous cycle data could also be caused by some effect other than the bath tub effect. In any case, Figure 2-7 indicates that the failure probability model is describing the trend of time since previous cycle reasonably well.

Figure 2-8 shows the same dataset binned by previous-cycle test result. These plots are only for the data where the previous test was an ASM or neither ASM nor two-speed-idle test. The figure shows that when the previous ASM test was a fail, the subsequent ASM tests that were performed were more likely to be fails than if the previous-cycle ASM test was a pass. If the previous-cycle ASM test did not exist, then the fraction of ASM tests in the dataset had fail rates that were very similar to those vehicles that passed their previous-cycle ASM test. The similarity in fail rates for vehicles that had no previous-cycle test with those that had a passing previous-cycle test is expected since most vehicles pass the ASM test..

All of the 64 plots of the sort described here can be viewed in Appendix M for the 1986 to 2002 FNTE, Ford_Car, 3.0L_V6_N vehicles to look for consistency among the plots.

[22] This rapid decrease is supported by only a small number of observations.

3.0 Other Models Needed to Rank Vehicles

The previous section described the development of ASM failure probability models. While these models can be used to calculate ASM overall and ASM mode/pollutant failure probabilities, the models by themselves are not sufficient to describe the effect of an I/M program on failure probabilities and emissions of vehicles that participate in an I/M program. To describe the effect of participation and to be able to answer the main questions in this study, three other models are needed:

I/M Completion Probabilities – The VID history of individual vehicles reveals when the vehicles were inspected. From that information and the ASM failure probability models and using the techniques described previously, it is straightforward to calculate future failure probabilities and ASM and FTP emissions for the case where a vehicle no longer participates in the I/M program. But predicting these quantities in the future for a vehicle that continues participating in the I/M program is more difficult since we do not know when the individual vehicle will be inspected. However, by performing an analysis of the VID, we can calculate the probability that the vehicle will receive an ASM inspection in any given month in the future. By combining these I/M completion probabilities with the techniques described in the previous section, it becomes straightforward to calculate future monthly ASM failure probabilities, estimated ASM emissions, and estimated FTP emissions for individual vehicles.

Estimating Monthly Miles Driven – Vehicles that drive more miles per month are a greater risk to the airshed from tailpipe emissions than vehicles that drive very little. Since we can now estimate FTP emission rates (grams per mile), if we can also estimate monthly miles driven for individual vehicles, we would be able to estimate FTP mass emissions in the future for individual vehicles. Another quantity that we would like to calculate is the risk to the I/M program of vehicles that are driving in an overall ASM-failed status. The quantity that the I/M program wants to minimize is the failed miles driven each month, which is the instantaneous overall ASM failure probability times the monthly miles driven.

Estimating Vehicle Market Value – Market value is important when considering vehicle scrappage. We can rank vehicles to optimally identify the best Scrapping candidates by calculating the expected FTP emissions reduction divided by the vehicle market value. In general, we would expect that vehicle owners would accept market value for their vehicles.

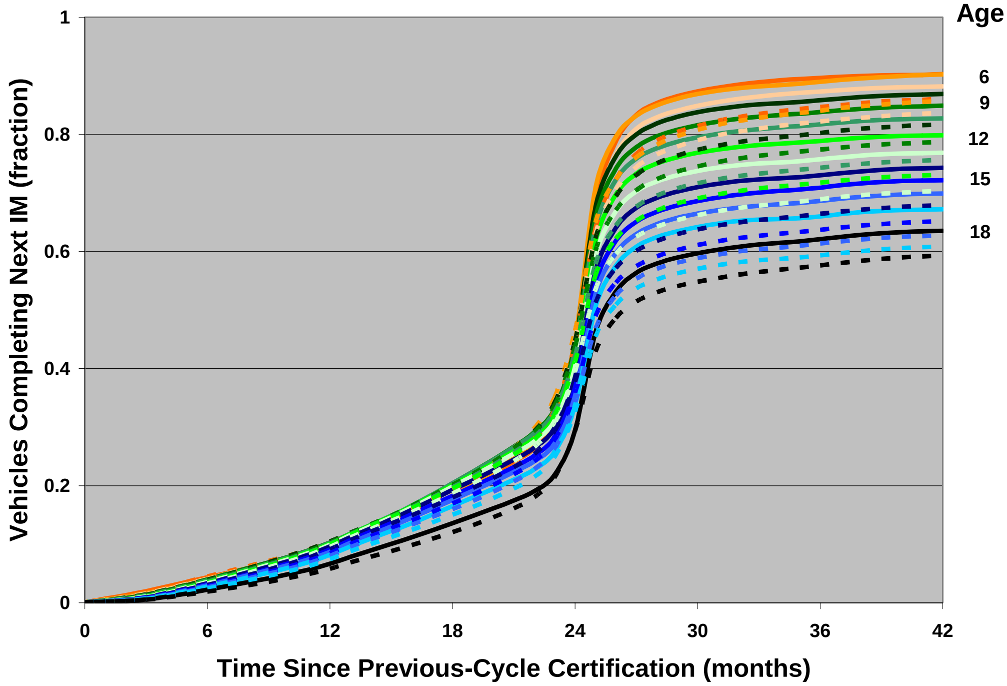
3.1 I/M Requirement Completion Probabilities

To calculate future ASM failure probabilities for a vehicle that is participating in an I/M program, we need to be able to estimate the probability that a vehicle will complete its next-cycle I/M requirements in any given month as a function of the VID history of the vehicle. We call these I/M completion probabilities Cprobs. Since California's I/M program is a biennial program, we expect that a large number of vehicles will return for their next inspection on the biennial anniversary of a previous inspection. However, some vehicles return earlier than their 24-month anniversary for a change of ownership inspection. Other vehicles are late and are, therefore, inspected more than 24 months after their previous-cycle inspection. Still other vehicles do not return for inspection at all. They have either left the I/M area or are, for some reason, no longer participating the I/M program.

We performed an analysis of the historical ASM VID to determine the cumulative ASM completion probabilities as a function of time since the previous inspection, the age of the vehicle, and whether the vehicle passed or failed its previous I/M inspection[23]. A plot of the cumulative Cprobs is shown in Figure 3-1 as a function of time since previous-cycle certification. Each curve represents the Cprobs for a vehicle of a constant age that had passed or failed its previous-cycle initial-test ASM. Solid lines are for vehicles that previously passed; dashed lines are for vehicles that previously failed. The curves show a rapid rise in completion probability around 24 months since the previous-cycle certification. This feature is a result of many vehicles returning on their 24-month anniversary. Curves of the same color denote vehicles of the same age. The curves show that, at the longest times, the Cprobs plateau. The value at the plateau depends on vehicle age and previous-cycle pass/fail result. For example, for 6-year-old vehicles about 90% of the vehicles ultimately return for their next inspection. On the other hand, for 18-year-old vehicles, only about 65% return for their next inspection. The curves also indicate that, for a given age vehicle, vehicles that passed their previous-cycle initial ASM are about 4% more likely to ultimately return for their next inspection than vehicles that failed their previous-cycle initial ASM.

[23] The programs that made these calculations are /bigrig/DecisionModel/CompleteIMReqt/CompleteIMReqt_step1.sas and CompleteIMReqt_step2.sas. The resulting I/M completion requirement Cprobs are stored in a file called /bigrig/DecisionModel/CompleteIMReqt/CmpltIMProb.csv.

Figure 3-1. I/M Requirement Completion Curves



From an I/M program improvement perspective, we would want to know what happened to the vehicles that did not return for an I/M inspection. If the vehicles left the I/M area, then they would no longer be emitting in the area. However, if the vehicles continued to drive in the I/M area illegally, then their emissions, which would not be "controlled" by the I/M program, would contribute to the airshed. The portion of vehicles that do not return, as indicated by the Cprob curves not reaching 100% in Figure 3-1, represent an inefficiency of the I/M program because of lack of complete enforcement and/or fleet coverage. In this study, we will not be concerned with those vehicles that do not return for inspection even though their emissions may be important contributors to the airshed. Consideration of those vehicles is left for another study. The vehicles that we are investigating in this study are those that do return for ASM inspection. We know they returned because we have an ASM following an RSD for them in the pilot dataset.

Application of the Cprobs to ranking of vehicles for Directing, Exempting, Calling-In, and Scrapping is different for analysis of the pilot dataset and for field applications. In the case of field applications, it is not known in advance whether vehicles will actually return for their next I/M inspection. On the other hand, in the pilot dataset, we know that vehicles returned. Otherwise, that particular observation would not be in the pilot dataset. In the discussion here, we will only be concerned with use of the Cprobs for analysis and ranking using the pilot dataset.

The following two examples demonstrate how the cumulative Cprobs are used in the analysis. As we will see later in the report, ranking of vehicles for a particular question affects how the Cprobs are used. The Cprobs are used differently for the cases where a new certification is issued at the decision point and where a new certification is not issued at the decision point. If a new certification is issued, we call the Cprobs pink; if no new certification is issued at the decision point, we call the Cprobs brown. As shall be shown later in this report, pink Cprobs are used for Directing, Exempting, and Calling-In Sticker. Brown Cprobs are used for Calling-In No-Sticker, Scrapping, and the Normal I/M Process. To use either kind of Cprob in the calculations, we need to calculate differential Cprobs, which give the probability that a vehicle will complete its I/M requirement in a particular month. It is these ΔCprobs that are used in ranking calculations.

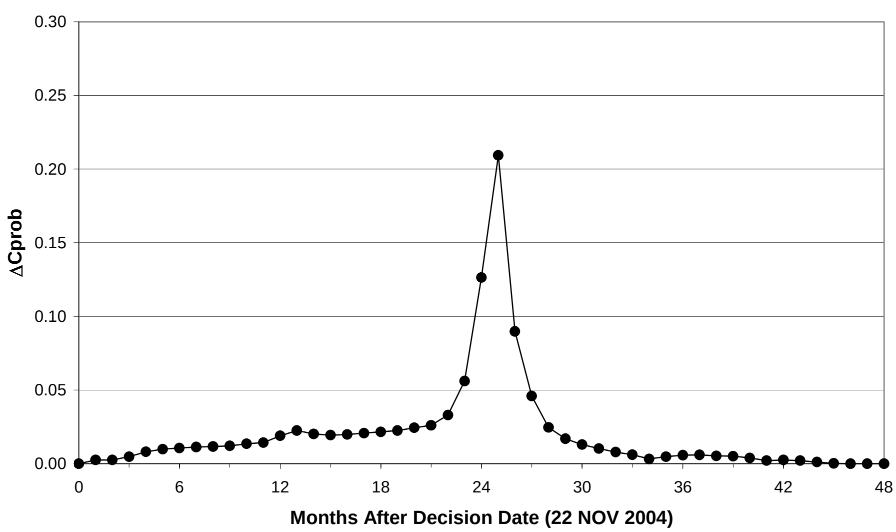
First, let us consider the case of pink Cprobs. Suppose we wanted to rank the vehicle for Directing, Exempting, or Calling-In Sticker. In all three situations, since a new certification is issued, the owner would be starting at the beginning of one of the cumulative Cprob curves shown in Figure 3-1. To determine which curve, let us consider a specific vehicle, VIN = 1FABP50U7JG198918, which had an RSD reading made on November 22, 2004. At the time of the RSD, the vehicle was 16.9 years old, assuming a vehicle birthdate of January 1, 1988, its model year. Let us assume that the vehicle would fail an ASM test at the time of the decision. Therefore, the cumulative Cprobs for a 17-year-old vehicle that previously failed are retrieved from the Cprob data file and are shown in the fourth column of Table 3-1. To calculate the ΔCprobs, in this study we are selecting the first 48 months of the Cprob curve. Therefore, the relevant Cprobs for the calculations are shown in the fifth column of Table 3-1. In Month 48 of After Previous-Cycle Certification we see that the relevant Cprob is 0.6110, which is the probability that a vehicle would return within 48 months for its next inspection. However, since the vehicle did return (because it is in the pilot dataset), this value should really be 1. Therefore, we normalize the Cprobs to create the sixth column. In the last step we take the differences of adjacent-month normalized Cprobs to obtain ΔCprob in the last column of the table. These pink ΔCprobs are plotted in Figure 3-2. The plot shows the pink ΔCprobs for each month after the decision. The vehicle is most likely to return for its next inspection about 24 months after the decision which is as expected since the vehicle would receive a new certification at the decision point.

Table 3-1. Differential I/M Completion Probabilities for Directing, Exempting, and Calling-In Sticker (Pink ΔCprob)

Date	Months After Previous-Cycle Certification	Months After Decision Date	Cprob (17 yrs old, Failed Previously)	Relevant Cprob	Normalized Cprob	ΔCprob
Nov-04	0	0	0.0008	0.0008	0.0014	0.0014
Dec-04	1	1	0.0024	0.0024	0.0040	0.0026
Jan-05	2	2	0.0040	0.0040	0.0065	0.0026
Feb-05	3	3	0.0069	0.0069	0.0113	0.0047
Mar-05	4	4	0.0118	0.0118	0.0194	0.0081
Apr-05	5	5	0.0179	0.0179	0.0292	0.0099
May-05	6	6	0.0243	0.0243	0.0398	0.0106
Jun-05	7	7	0.0312	0.0312	0.0511	0.0113
Jul-05	8	8	0.0384	0.0384	0.0628	0.0117
Aug-05	9	9	0.0457	0.0457	0.0749	0.0121
Sep-05	10	10	0.0540	0.0540	0.0884	0.0136
Oct-05	11	11	0.0628	0.0628	0.1027	0.0143
Nov-05	12	12	0.0743	0.0743	0.1216	0.0189
Dec-05	13	13	0.0881	0.0881	0.1441	0.0225
Jan-06	14	14	0.1004	0.1004	0.1643	0.0202
Feb-06	15	15	0.1122	0.1122	0.1837	0.0194
Mar-06	16	16	0.1243	0.1243	0.2035	0.0198
Apr-06	17	17	0.1370	0.1370	0.2243	0.0208
May-06	18	18	0.1502	0.1502	0.2459	0.0216
Jun-06	19	19	0.1640	0.1640	0.2684	0.0225
Jul-06	20	20	0.1788	0.1788	0.2927	0.0243
Aug-06	21	21	0.1948	0.1948	0.3188	0.0261
Sep-06	22	22	0.2150	0.2150	0.3518	0.0330
Oct-06	23	23	0.2492	0.2492	0.4079	0.0561
Nov-06	24	24	0.3264	0.3264	0.5343	0.1263
Dec-06	25	25	0.4543	0.4543	0.7435	0.2093
Jan-07	26	26	0.5091	0.5091	0.8333	0.0898
Feb-07	27	27	0.5371	0.5371	0.8792	0.0458
Mar-07	28	28	0.5522	0.5522	0.9038	0.0246
Apr-07	29	29	0.5625	0.5625	0.9207	0.0169
May-07	30	30	0.5704	0.5704	0.9336	0.0129
Jun-07	31	31	0.5767	0.5767	0.9439	0.0103
Jul-07	32	32	0.5815	0.5815	0.9518	0.0078
Aug-07	33	33	0.5852	0.5852	0.9578	0.0061
Sep-07	34	34	0.5872	0.5872	0.9610	0.0032
Oct-07	35	35	0.5901	0.5901	0.9658	0.0047
Nov-07	36	36	0.5936	0.5936	0.9715	0.0058
Dec-07	37	37	0.5972	0.5972	0.9775	0.0059
Jan-08	38	38	0.6005	0.6005	0.9829	0.0054
Feb-08	39	39	0.6036	0.6036	0.9880	0.0051
Mar-08	40	40	0.6060	0.6060	0.9919	0.0039
Apr-08	41	41	0.6073	0.6073	0.9940	0.0021
May-08	42	42	0.6088	0.6088	0.9965	0.0025
Jun-08	43	43	0.6101	0.6101	0.9986	0.0021
Jul-08	44	44	0.6108	0.6108	0.9997	0.0012
Aug-08	45	45	0.6110	0.6110	1.0000	0.0002

Date	Months After Previous-Cycle Certification	Months After Decision Date	Cprob (17 yrs old, Failed Previously)	Relevant Cprob	Normalized Cprob	ΔCprob
Sep-08	46	46	0.6110	0.6110	1.0000	0.0000
Oct-08	47	47	0.6110	0.6110	1.0000	0.0000
Nov-08	48	48	0.6110	0.6110	1.0000	0.0000
Dec-08	49	49	0.6110		1.0000	
Jan-09	50	50	0.6118		1.0000	
Feb-09	51	51	0.6122		1.0000	
Mar-09	52	52	0.6130		1.0000	
Apr-09	53	53	0.6132		1.0000	
May-09	54	54	0.6137		1.0000	
Jun-09	55	55	0.6138		1.0000	
Jul-09	56	56	0.6138		1.0000	
Aug-09	57	57	0.6138		1.0000	
Sep-09	58	58	0.6138		1.0000	
Oct-09	59	59	0.6138		1.0000	
Nov-09	60	60	0.6138		1.0000	
Dec-09	61	61	0.6138		1.0000	
Jan-10	62	62	0.6138		1.0000	
Feb-10	63	63	0.6138		1.0000	
Mar-10	64	64	0.6138		1.0000	
Apr-10	65	65	0.6138		1.0000	
May-10	66	66	0.6138		1.0000	
Jun-10	67	67	0.6138		1.0000	
Jul-10	68	68	0.6138		1.0000	
Aug-10	69	69	0.6138		1.0000	
Sep-10	70	70	0.6138		1.0000	
Oct-10	71	71	0.6138		1.0000	
Nov-10	72	72	0.6138		1.0000	

Figure 3-2. Example of Pink ΔCprobs
(17-year old, Previously-Failing Vehicle)



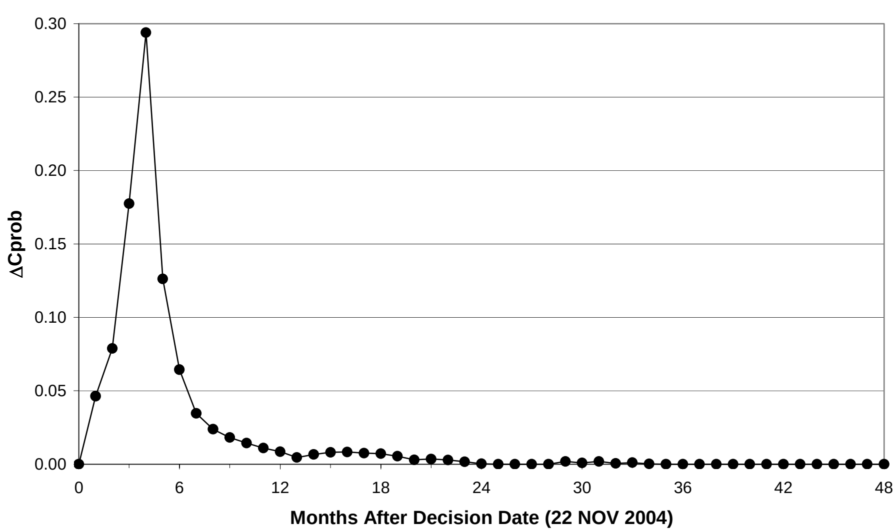
Now, consider the calculation of brown ΔCprobs for the same vehicle. The brown ΔCprobs would be used for Calling-In No-Sticker, the Normal I/M Process, and Scrapping. In this situation, no new certification is given to the vehicle. Therefore, the vehicle continues to be on the same cumulative Cprob curve that it has been on since his previous inspection, which was on February 15, 2003. At the time of that previous inspection, the vehicle was 15.1 years old and had failed that inspection. Therefore, we look up the cumulative Cprobs for a 15-year-old vehicle that had previously failed and place the values in the fourth column of Table 3-2. At the time of the decision, November 22, 2004, it has been 21 months since the previous inspection, and it is known from the VID records that the vehicle has not yet received the next-cycle initial-test ASM inspection since February 2003. Accordingly, the relevant Cprobs shown in the fifth column of Table 3-2 must be 0 for the first 20 months. Beginning with Month 21 of After Previous-Cycle Certification, the relevant Cprobs have the same values as the values in the fourth column for the next 48 months. Next, for the same reasons as in calculating the pink ΔCprobs, the relevant Cprobs are normalized to create the sixth column. This produces a new Cprob curve that goes smoothly from 0 in Month 21 to 1 in Month 69. Finally, adjacent-month normalized Cprobs are differentiated to produce the ΔCprob values in the last column of the table. These values are plotted in Figure 3-3. Again, the points in the plot give the probability that the vehicle will be inspected in any given month subject to the constraint that we know the vehicle did receive a subsequent inspection since the vehicle observation is in the pilot dataset.

Table 3-2. Differential I/M Completion Probabilities for Calling-In No-Sticker, Scrapping (Brown ΔCprob)

Date	Months After Previous-Cycle Certification	Months After Decision Date	Cprob (17 yrs old, Failed Previously)	Relevant Cprob	Normalized Cprob	ΔCprob
Feb-03	0	-21	0.0008		0.0000	
Mar-03	1	-20	0.0024		0.0000	
Apr-03	2	-19	0.0040		0.0000	
May-03	3	-18	0.0069		0.0000	
Jun-03	4	-17	0.0118		0.0000	
Jul-03	5	-16	0.0179		0.0000	
Aug-03	6	-15	0.0243		0.0000	
Sep-03	7	-14	0.0312		0.0000	
Oct-03	8	-13	0.0384		0.0000	
Nov-03	9	-12	0.0457		0.0000	
Dec-03	10	-11	0.0540		0.0000	
Jan-04	11	-10	0.0628		0.0000	
Feb-04	12	-9	0.0743		0.0000	
Mar-04	13	-8	0.0881		0.0000	
Apr-04	14	-7	0.1004		0.0000	
May-04	15	-6	0.1122		0.0000	
Jun-04	16	-5	0.1243		0.0000	
Jul-04	17	-4	0.1370		0.0000	
Aug-04	18	-3	0.1502		0.0000	
Sep-04	19	-2	0.1640		0.0000	
Oct-04	20	-1	0.1788		0.0000	
Nov-04	21	0	0.1948	0.1948	0.0367	0.0367
Dec-04	22	1	0.2150	0.2150	0.0831	0.0464
Jan-05	23	2	0.2492	0.2492	0.1619	0.0788
Feb-05	24	3	0.3264	0.3264	0.3393	0.1775
Mar-05	25	4	0.4543	0.4543	0.6333	0.2940
Apr-05	26	5	0.5091	0.5091	0.7594	0.1261
May-05	27	6	0.5371	0.5371	0.8238	0.0644
Jun-05	28	7	0.5522	0.5522	0.8584	0.0346
Jul-05	29	8	0.5625	0.5625	0.8822	0.0238
Aug-05	30	9	0.5704	0.5704	0.9003	0.0182
Sep-05	31	10	0.5767	0.5767	0.9148	0.0145
Oct-05	32	11	0.5815	0.5815	0.9258	0.0110
Nov-05	33	12	0.5852	0.5852	0.9343	0.0085
Dec-05	34	13	0.5872	0.5872	0.9388	0.0045
Jan-06	35	14	0.5901	0.5901	0.9455	0.0067
Feb-06	36	15	0.5936	0.5936	0.9536	0.0081
Mar-06	37	16	0.5972	0.5972	0.9619	0.0083
Apr-06	38	17	0.6005	0.6005	0.9695	0.0075
May-06	39	18	0.6036	0.6036	0.9767	0.0072
Jun-06	40	19	0.6060	0.6060	0.9821	0.0054
Jul-06	41	20	0.6073	0.6073	0.9851	0.0030
Aug-06	42	21	0.6088	0.6088	0.9886	0.0035
Sep-06	43	22	0.6101	0.6101	0.9916	0.0029
Oct-06	44	23	0.6108	0.6108	0.9932	0.0016
Nov-06	45	24	0.6110	0.6110	0.9935	0.0003

Date	Months After Previous-Cycle Certification	Months After Decision Date	Cprob (17 yrs old, Failed Previously)	Relevant Cprob	Normalized Cprob	ΔCprob
Dec-06	46	25	0.6110	0.6110	0.9935	0.0000
Jan-07	47	26	0.6110	0.6110	0.9935	0.0000
Feb-07	48	27	0.6110	0.6110	0.9935	0.0000
Mar-07	49	28	0.6110	0.6110	0.9936	0.0000
Apr-07	50	29	0.6118	0.6118	0.9954	0.0019
May-07	51	30	0.6122	0.6122	0.9963	0.0009
Jun-07	52	31	0.6130	0.6130	0.9982	0.0019
Jul-07	53	32	0.6132	0.6132	0.9988	0.0006
Aug-07	54	33	0.6137	0.6137	0.9998	0.0011
Sep-07	55	34	0.6138	0.6138	1.0000	0.0002
Oct-07	56	35	0.6138	0.6138	1.0000	0.0000
Nov-07	57	36	0.6138	0.6138	1.0000	0.0000
Dec-07	58	37	0.6138	0.6138	1.0000	0.0000
Jan-08	59	38	0.6138	0.6138	1.0000	0.0000
Feb-08	60	39	0.6138	0.6138	1.0000	0.0000
Mar-08	61	40	0.6138	0.6138	1.0000	0.0000
Apr-08	62	41	0.6138	0.6138	1.0000	0.0000
May-08	63	42	0.6138	0.6138	1.0000	0.0000
Jun-08	64	43	0.6138	0.6138	1.0000	0.0000
Jul-08	65	44	0.6138	0.6138	1.0000	0.0000
Aug-08	66	45	0.6138	0.6138	1.0000	0.0000
Sep-08	67	46	0.6138	0.6138	1.0000	0.0000
Oct-08	68	47	0.6138	0.6138	1.0000	0.0000
Nov-08	69	48	0.6138	0.6138	1.0000	0.0000
Dec-08	70	49	0.6138		1.0000	
Jan-09	71	50	0.6138		1.0000	
Feb-09	72	51	0.6138		1.0000	

Figure 3-3. Example of Brown ΔCprobs (17-year-old, Previously-Failing Vehicle)



3.2 Estimating Monthly Miles Driven

One of the risk factors for automotive tailpipe emissions is the number of miles that a vehicle is driven each month. Vehicles that are not driven at all have no tailpipe emissions. Vehicles that are driven a large number of miles in each month can produce a large mass of emissions even if the vehicles are relatively low emitting on a per mile basis. In this study, we use monthly miles driven to convert overall ASM failure probability to monthly failed miles driven and to convert FTP emission rates in grams per mile to monthly FTP mass emissions.

In this study we have used the annual vehicle miles traveled shown in Table 3-3 to calculate monthly miles driven based on vehicle age. The values shown in the table were obtained from EMFAC. A more vehicle-specific measure of monthly miles driven can be obtained from VID odometer readings. While the odometer readings recorded in the VID for individual vehicles are known to contain typographical and rollover errors, we believe that most of these types of errors can be corrected with computer routines by considering the odometer readings over the full VID history of the vehicle. The development of this odometer correction routine was not completed in this study and, therefore, we reserve that work for a future effort.

Another future work effort is reserved for the development of monthly miles driven tables for use in the Scrapping algorithm. To properly estimate the benefits of scrappage, vehicles need to be ranked by taking into account not only the number of miles that they currently drive in each month, but also the number of miles that will be driven in the remaining life of the vehicle and the time period over which that driving will take place. Such vehicle annuity tables would be based on the current age of the vehicle and the current odometer reading of the vehicle. The Scrapping benefits would be calculated for not just the 24 months following the Scrapping decision but for the estimated remaining life of the vehicle.

Table 3-3. EMFAC Estimate of Annual Miles Driven

Vehicle Age (years)	Annual Miles Driven
1	17,386
2	16,524
3	15,803
4	15,162
5	14,564
6	13,999
7	13,496
8	13,061
9	12,650
10	12,257
11	11,873
12	11,499
13	11,139
14	10,797
15	10,459
16	10,162
17	9,885
18	9,605
19	9,320
20	9,078
21	8,813
22	8,557
23	8,288
24	8,133
25	7,910
26	7,692
27	7,545
28	7,354
29	7,242
30	7,049
31	6,950
32	6,706
33	6,511
34	6,337
35	6,107
36	5,933
37	5,684
38	5,446
39	5,188
40	5,066
41	4,941

3.3 Estimating Vehicle Market Value

For the purposes of creating a vehicle Scrapping candidate list, we need to estimate the current market value of all vehicles at the time that the decision to make a scrappage offer to the vehicle owner is made. We believe that the market value is a reasonable estimate of the amount that the owner would expect to receive if the State wanted to scrap a vehicle. We believe that scrappage offers should be based on the size of expected reductions of mass emissions and vehicle market value rather than using fixed scrappage offer amounts. The I/M program would want to offer an amount that is larger than the traditional fixed scrappage offer if the vehicle is expected to be a particularly high-emitting vehicle over its remaining lifetime.

We estimated the market value of all vehicles in the pilot dataset by estimating the median new vehicle price as a function of Make_CarTrk and then applying a vehicle depreciation factor that was a function of vehicle age and Make_CarTrk. We used the 2002 Automotive News Market Data book to look up base new-vehicle prices for different models or series within each Make_CarTrk category. To minimize the influence of unusually low or unusually high values of new vehicles within Make_CarTrk, we calculated the median price of the different lines or series within Make_CarTrk. The resulting median values are shown in Table 3-4.

Table 3-4. Median 2002 New Vehicle Price by Make_CarTrk

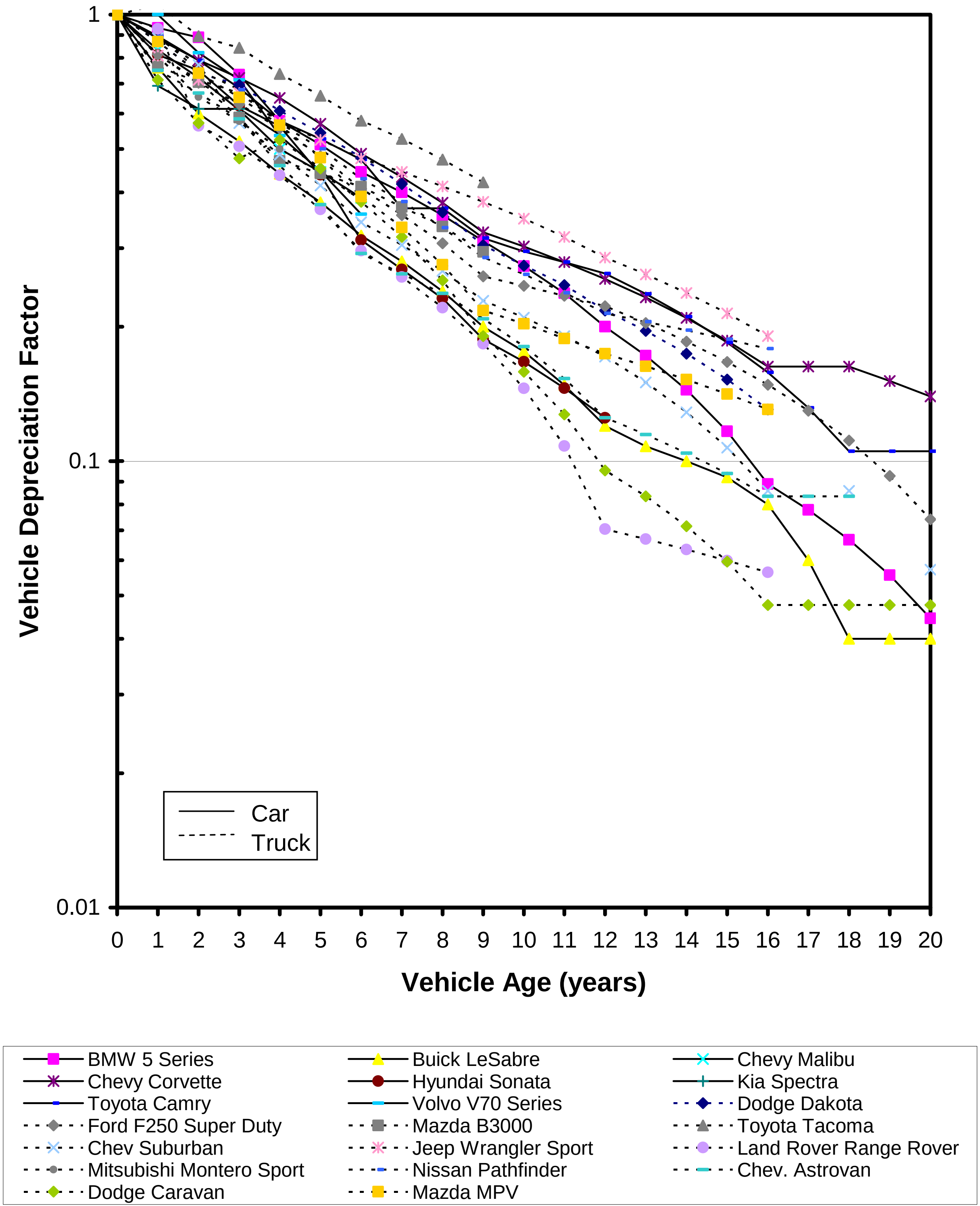
Make_CarTrk	Median 2002 New Vehicle Price ($1,000)
ACURA_CAR	37
ACURA_TRK	35
ALFAROMEO_CAR	39
AMERICAN_CAR	20
AMERICAN_TRK	20
AUDI_CAR	40
BMW_CAR	48
BMW_TRK	57
BUICK_CAR	27
CADILLAC_CAR	45
CADILLAC_TRK	50
CHEV/SUZUKI_CAR	15
CHEVROLET_CAR	20
CHEVROLET_TRK	30
CHRYSLER_CAR	25
CHRYSLER_TRK	30
DAEWOO_CAR	13
DATSUN_CAR	19
DATSUN_TRK	15
DODGE/MITS_CAR	21
DODGE/MITS_TRK	29
DODGE_CAR	22
DODGE_TRK	23
EAGLE_CAR	23
FERRARI_CAR	240
FORD/MAZDA_CAR	21
FORD_CAR	22
FORD_TRK	27
FORDTRUCK_TRK	27
GMC_CAR	30
GMC_TRK	30
HONDA_CAR	22
HONDA_TRK	23
HYUNDAI_CAR	16
HYUNDAI_TRK	21
INFINITI_CAR	29
ISUZU_CAR	21
ISUZU_TRK	28
JAGUAR_CAR	68
JEEP_TRK	22
KIA_CAR	12
LANDROVER_TRK	35
LEXUS_CAR	44
LEXUS_TRK	36
LINCOLN_CAR	43
LINCOLN_TRK	53
MAZDA_CAR	21
MAZDA_TRK	22
MERCEDES_CAR	59
MERCEDES_TRK	57

Make_CarTrk	Median 2002 New Vehicle Price ($1,000)
MERCURY_CAR	22
MERCURY_TRK	31
MERKUR_CAR	22
MITSUBISHI_CAR	21
MITSUBISHI_TRK	29
NISSAN_CAR	19
NISSAN_TRK	25
OLDSMOBILE_CAR	26
OLDSMOBILE_TRK	35
PEUGEOT_CAR	39
PLYM/MITS_CAR	21
PLYMOUTH_CAR	22
PLYMOUTH_TRK	23
PONTIAC_CAR	21
PONTIAC_TRK	23
PORSCHE_CAR	81
ROLLSROYCE_CAR	269
SAAB_CAR	39
SATURN_CAR	17
STERLING_CAR	40
SUBARU_CAR	23
SUZUKI_CAR	15
SUZUKI_TRK	22
TOYOTA_CAR	20
TOYOTA_TRK	26
VOLVO_CAR	34
VW_CAR	21
VW_TRK	27

The source of the data for vehicle depreciation, as a function of vehicle age, was obtained for 20 different specific vehicle models using dealer values as obtained from Kelly Blue Book (kbb.com). To simulate the effect of vehicle aging, we used dealer prices from older model-year vehicles. In several cases, it was necessary to switch to comparable models within the make as new models were manufactured in place of models that were discontinued. In general, we found that vehicle value depreciated with an exponential decay. Figure 3-4 shows the vehicle values expressed relative to the new car value for 20 different car and truck models. The plot shows a range of differences in depreciation over the 20 year period. For the purposes of this study, we needed to calculate a decay constant for cars and a decay constant for trucks. We used a SAS program[24] to calculate the decay constant of -0.134 year^{-1} for cars and -0.170 year^{-1} for trucks to describe the exponential decay.

[24] /bigrig/DecisionModel/ASMFprob2005/ValueOfVehs.sas

Figure 3-4. Depreciation Factor for Selected Vehicles



Using these analyses, the estimated value of a vehicle is given by:

$$\text{Value} = \text{New Car Value} * \exp(k * \text{vehicle age})$$

where:

New Car Value is taken from Table 3-4, and

$k = -0.134\ \text{year}^{-1}$ for cars
$\quad = -0.170\ \text{year}^{-1}$ for trucks

Figure 3-4 seems to indicate that the spread of depreciation rates among car models and among truck models may larger than the difference in average depreciation rates between cars and trucks. Thus, adding vehicle model to the look-up of the depreciated values of vehicles in addition to age, make, and vehicle type could be expected to result in further improvements in the efficiency of vehicle selection for Scrapping. An additional factor that was not included in this analysis is the further reduction in vehicle value that is associated with a vehicle that has failed its current I/M emissions inspection.

4.0 Approach for Ranking Variables for Four Questions

In the previous two sections, we described the development of six different models that predict overall ASM failure probability and models for I/M completion probabilities, estimating monthly miles driven, and estimating vehicle market value. In this section, we will describe how these models can be put together to calculate quantities to rank individual vehicles for priority selection for Directing, Exempting, Calling-In, and Scrapping.

In Section 4.1 we describe the three different ranking criteria and their special features. Section 4.2 describes the detailed methods for combining the ASM failure probability models and the supporting models to arrive at values for forecasted overall ASM failure probability and forecasted FTP emissions for the Normal I/M Process, Directing, Exempting, Calling-In No-Sticker, Calling-In Sticker, and Scrapping as a function of time after the decision point. Section 4.3 describes how the forecasted failure probabilities and forecasted FTP emissions calculated in Section 4.2 are combined to produce the values used for ranking individual vehicles for selection for Directing, Exempting, Calling-In No-Sticker, Calling-In Sticker, and Scrapping. Section 4.4 compares the ranking values calculated by the different ranking methods. Finally, Section 4.5 describes how the models are used to calculate forecasted probable repair costs for individual vehicles.

4.1 Individual Vehicle Ranking Criteria

Three criteria are used in this study to rank individual vehicles in the pilot dataset for evaluation of efficiency-improvement strategies. The first criterion is the traditional one. In addition, we have developed two new criteria that provide substantial benefits over the traditional approach. The three ranking criteria used in this study are:

- Overall ASM failure probability at the decision point;
- Change in failed miles driven (ΔFMD) calculated over 24 months after the decision point; and
- Change in FTP mass emissions calculated over 24 months after the decision point per dollar of vehicle value (ΔFTP/$).

Table 4-1 compares the features of the three ranking criteria from the point of view of the factors that influence their ability to rank vehicles. These features for each ranking criterion are discussed below. The dataset used for this study included some records with multiple RSD measurements on individual vehicles. As mentioned earlier, when building the Fprob models, we treated these records as if they had been obtained on separate, but identical, vehicles. Similarly, when it came to ranking vehicles, we also ranked the records as if they had been obtained on separate, but identical, vehicles.[25] Clearly, multiple RSD measurements on a single vehicle provide more information than if only one RSD measurement were available; however, the proper way to handle multiple RSD measurements is not obvious. We leave the consideration of multiple RSD measurements to a future project.

Table 4-1. Features that the Three Ranking Criteria Consider

	Ranking Criterion		
Features Considered	**Fprob at Decision Point**	**Change in Failed Miles Driven Over 24 Months After the Decision Point (ΔFMD)**	**Change in FTP Mass Emissions Over 24 Months After the Decision Point per Vehicle Value Dollar (ΔFTP/$)**
Probability of ASM Failure at the Decision Point	X	X	X
When the next inspection is expected		X	X
Changes caused by I/M-Program-Induced repairs		X	X
Changes caused by After-Inspection Emissions Degradation		X	X
Changes caused by Vehicle Aging		X	X
Effects of Monthly Miles Driven		X	X
Current Vehicle Value		n/a	X
Mass Emissions		n/a	X
Which question is to be answered		X	X

Fprob at Decision Point – The traditional ASM overall Fprob has been used for a number of years to direct vehicles to high-performing stations just before their biennial anniversary. Vehicles with high Fprob values were directed. Analogously, for the questions

[25] Consider the example of two vehicles that each received three RSD hits. The first has three high RSDs; the second has only one high RSD. The first vehicle is more likely to be a true high emitter and therefore should be ranked higher. Because our Fprob models were built on the separate data from these vehicles, the models would be more likely to select all three of the records from the first vehicle, but just one record of the second vehicle. At the time of evaluation of the emissions benefits, the estimated FTP emissions derived from all three of the first vehicle's records but from only one of the second vehicle's record would be selected. Accordingly, the difference in the total estimated FTP emissions records selected would reflect the likely emissions captured by an intervention activity. Therefore, the models emulate the real application of the models to multiple RSD measurements - although not perfectly.

asked in this study, Fprob at Decision Point provides a single ranking value for each vehicle based only on a failure probability at one point in time – the time of the decision. Depending on the model that is used to calculate that Fprob, the value may take into account vehicle description, model year, VID history, and/or RSD measurements. Regardless of which "fancy" model is used to calculate the overall Fprob, Fprob at the Decision Point looks only at the probability of failing at that single point in time. It does not look into the future in any way. Fprob at Decision Point does not consider when the vehicle might get its next ASM inspection. It doesn't look at how emissions or the failure probability might change if a repair is made. It doesn't look at how emissions or failure probability might degrade after a potential repair is completed. It doesn't look at how many miles the vehicle drives each month. It doesn't consider the effect of vehicle aging, and for Scrapping, it doesn't look at the vehicle market value or consider the mass of FTP emissions that would be reduced.

Because Fprob at Decision Point does not consider the future in any way, there is no way to consider the specifics of how different I/M program improvement strategies affect the ranking of vehicles. With Fprob at Decision Point, there is simply one ranking. Vehicles with high Fprobs would be targeted for calling-in whether a new certification was issued or not, for Scrapping whether the vehicle is worth a lot or a little, and for Directing even if the vehicle is driven only 10 miles a month. Vehicles with low failure probabilities would be exempted even if they drive thousands of miles a month.

Historical VID data indicate, as shown in Figure 2-1, that the reduction in emissions concentrations observed at the single point in time when a vehicle is inspected and repaired is a crude estimator of the long-term benefits of inspecting individual vehicles. It follows that Fprob at Decision Point should be a low performance quantity for use in ranking vehicles for intervention to the Normal I/M Process.

Overall ASM failure probability at the decision point does have its advantages, however. Since it is calculated at one point in time, it is relatively easy to calculate. Second, it is relatively easy to verify since ASM inspections, which are also made at only one point in time, can be used for verification. The third advantage is that using this quantity minimizes the number of false intervention calls. For example, if Fprob at Decision Point is used to direct vehicles to high-performing stations,[26] the fraction of vehicles that fail the overall ASM test at the high-

[26] A hypothetical category of California I/M inspection station that would perform more-accurate I/M inspections and therefore would be able to provide greater emissions reductions than average-performing stations. In the analysis we did not attempt to determine which stations or which types of stations (Test Only, Test-and-Repair, Gold Shield, etc.) were average- or high-performing. Instead, based on station-performance information from BAR,

performing stations will be larger than by any other ranking method. The only question that remains is the size of the trade-off: By using this low performance ranking quantity, how many extra tons of FTP emissions are allowed into the airshed to avoid a little bit of embarrassment. In this study, we hope to evaluate this trade-off.

Fprob at Decision Point can be calculated for all six models: A, B, C, D, E, and F. Separate ranking values were calculated for each vehicle in the pilot dataset using the Fprob at Decision Point ranking criterion and using all six models, so that the performance of these combinations can be compared with the performance of other ranking criteria.

Change in Failed Miles Driven (ΔFMD) Over 24 Months After the Decision Point – We have developed this ranking criterion to "retain" the one feature that Fprob at Decision Point provides, that is, the probability of failing the ASM test at the decision point. But, in addition, this new criterion has many important features that Fprob at Decision Point does not have. This new ranking criterion was designed specifically for Directing, Exempting, and Calling-In. Because the name, Change in Failed Miles Driven Over 24 Months After the Decision Point, is so long, we will use ΔFMD as a shortened name, which stands for change in Failed Miles Driven.

As shown in Table 4-1, ΔFMD considers the probability of failing the ASM at the time of the decision point but it also considers when the next I/M inspection might be, how the emissions or the failure probability might change if a repair is made, how the emissions or failure probability might degrade after a potential repair is made, and how many miles the vehicle drives every month, and it includes vehicle aging. ΔFMD uses forecasted overall ASM failure probabilities and forecasted I/M completion probabilities plus estimated monthly miles driven[27] to calculate failed miles driven for each of the 24 months after the decision point. ΔFMD can be calculated only for Models C and D because only these models are time dependent and, therefore, only they can be used to forecast the 24 months after the decision point. Because Models A, B, E, and F have no time dependence, their Fprobs are the same for all months in the future. Accordingly, the values for ΔFMD using these models are all zero and those four models cannot be used to rank using the ΔFMD method.

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subsequent reports will assume that the hypothetical high-performing stations have fail rates that are somewhat higher and after-repair emissions levels that are somewhat lower than those of average-performing stations.

[27] The calculations in this study use EMFAC monthly mileage accumulation rates, which are based on vehicle age, to determine each vehicle's monthly miles driven. An improved method would be to use the VID records of each individual vehicle to determine each vehicle's monthly miles driven.

ΔFMD ranks vehicles based on the expected change in the failed miles driven over the 24 months after the decision point that would be produced by intervention in the Normal I/M Process. These calculations are done for two paths: the Normal I/M Process path, and the intervention path. The calculations for the Normal I/M Process path give failed miles driven for each month for the situation where vehicle participation in the I/M program is uninterrupted, that is, for the case where there is no Calling-In, Directing, or Exempting. The intervention path is calculated for each of three possible interventions: Directing and Exempting, which as it turns out have the same path, Calling-In Sticker, in which a new certification is given to the vehicle after meeting the call-in requirements, and Calling-In No-Sticker, in which the vehicle continues to follow the requirements of its previous-cycle certification even though the vehicle has met the requirements of the call-in ASM. Then, to arrive at the ΔFMD, the difference between the Normal I/M Process failed miles driven and the intervention failed miles driven are subtracted month-by-month and summed. To produce the ΔFMD, which is the failed-miles-driven benefit of the intervention, the subtraction is always done so that a negative ΔFMD indicates that the intervention produces a lower number of failed miles driven over 24 months.

Another benefit of the ΔFMD is that it considers the details of the intervention method. As shall be shown below, the forecasted overall ASM failure probabilities for the Normal I/M Process, Directing, Exempting, Calling-In Sticker, and Calling-In No-Sticker are all different and, therefore, the ΔFMDs for the different types of intervention are different. This means that vehicle targeting will be specific to the objective of the intervention.

Change in FTP Mass Emissions Over 24 Months After the Decision Point Per Vehicle Value Dollar (ΔFTP/$) – This ranking criterion is used only for ranking vehicles for Scrapping because of the special objective of Scrapping. When considering Scrapping, the State is purchasing a permanent reduction in the total emissions (that is, not just the excess emissions) of the vehicle that would occur during its remaining life. Because the State has a limited budget for purchasing vehicles for scrappage, the top candidates for Scrapping would be those that would have the largest total emissions. Accordingly, the best "bargains" would be those vehicles whose scrappage would produce the largest drop in FTP mass emissions for each dollar spent by the State.

The probability of failing an ASM test is not a good quantity to base Scrapping candidates on. One of the reasons for this is that old vehicles, which tend to have high overall emission rates, also have high cutpoints. Therefore, their failure probabilities can be relatively lower than other vehicles – even though their total emissions are higher. Consequently, for

Scrapping, total emissions is more important than failure probability. Of course, failure probability at the time of a scrappage ASM is still important because vehicles that do not fail a scrappage ASM test would not be offered the scrappage package.

Overall, the ΔFTP/$ ranking criterion considers not only the probability of failing the scrapping ASM test at the decision point but it also considers when the next inspection of the vehicle might occur, how the emissions or failure probability might change if a repair is made, how the emissions or failure probability might degrade after a potential future repair, how many miles the vehicle is driven every month, vehicle aging, the estimated market value of the vehicle, and the reduction in FTP mass emissions over the 24 months after the decision if the vehicle were scrapped.

One nuance in developing the ΔFTP/$ ranking variable is the question of whether vehicles should be selected based on estimated FTP HC, FTP CO, or FTP NX mass emissions or a combination of the three emissions. Rather than try to pick an arbitrary method of combining FTP mass emissions into a single value, for the purposes of this study, we simply created one ΔFTP/$ variable for each of the three FTP emission types: HC, CO, and NX. Then, when the results of the rankings are evaluated, we will be able to determine if the different types of ΔFTP/$ ranking variables have an important effect on the benefits of Scrapping.

As shown in Table 4-1, ΔFTP/$ also considers all of the important features that make sense when ranking vehicles for Scrapping. One feature that is not listed in Table 4-1 that potentially is important for Scrapping is the remaining life of the vehicle both in terms of miles driven and years. The calculations in this study assume that the miles driven by Scrapping candidates are constant over the 24 months after the scrappage decision and then drop to zero. Improving this aspect of the Scrapping calculations will be left for another study.

ΔFTP/$ can be calculated using only Models C, D, and E. The reason for this is that only these three models have ASM mode/pollutant cutpoint dependences which are required to do the integrations that estimate ASM mode/pollutant emission concentrations and, in turn, estimate FTP HC, CO, and NX emissions. Normally, only models, such as C and D, that have time dependences could be used to forecast time-dependent FTP mass emissions after the decision point. However, as it turns out, Model E, which does not have a time dependence, can also be used to rank vehicles for Scrapping because of the way that the model interacts with the Scrapping ranking algorithm, which will be shown in the next subsection. Models A, B, and F cannot be used to calculate ΔFTP/$ to rank vehicles for Scrapping because, since they do not contain cutpoint functionalities, these models cannot be integrated with respect to cutpoint to produce FTP emissions estimates.

4.2 Forecasting Failed Miles Driven and FTP Mass Emissions

The previous subsection described the three ranking criteria that will be used in this study. This subsection describes how the failure probability models, the I/M completion probability model, and the other techniques are used to calculate failed miles driven (FMD) and FTP mass emissions for individual vehicles for the different decision choices: Directing, Exempting, Calling-In No-Sticker, Calling-In Sticker, Scrapping, and the Normal I/M Process. Then, in the next section, the quantities calculated here will be contrasted and these differences will be ranked to arrive at the anticipated benefits of targeting individual vehicles for different types of intervention.

The approach described in this section does not apply to the first ranking criterion, which is Fprob at Decision Point, since that ranking criterion does not use any forecasting. For that ranking method, the overall ASM failure probability at the decision point is just calculated using whichever ASM failure probability model is to be used for ranking. That ranking method will not be discussed any further in this subsection or the next subsection.

On the other hand, the other two ranking criteria, ΔFMD and ΔFTP/$, can both take advantage of the time-dependence capabilities of Models C and D. In addition, Model E can be used to evaluate ΔFTP/$. In the discussion below, we concentrate on the details of how these forecasts are made. The discussion first describes how FMD is calculated for the Normal I/M Process, Directing, Exempting, Calling-In No-Sticker, and Calling-In Sticker. Then, the discussion shifts to providing the details of the calculations that forecast FTP mass emissions for the Normal I/M Process and Scrapping.

There is one concept that is used again and again in the calculations. This is the idea of "blending" probabilities. In some situations, future probabilities can be calculated by using historical ASM test results as the inputs for the failure probability models. For example, calculating the overall ASM failure probability for a hypothetical call-in ASM test is easily made by using the previous-cycle ASM inspection results, which are recorded in the VID, as inputs to the appropriate failure prediction model. However, we will want to also know the failure probabilities for the vehicle for each of the 24 months after the call-in ASM test. How can we calculate these probabilities if we don't know what the result of the call-in ASM test will be? This is where the idea of blending probabilities comes in. What we do is calculate the failure probabilities for each of the 24 months after the call-in ASM assuming that the call-in ASM is a pass, and we also calculate a separate set of 24 future-month failure probabilities assuming that the call-in ASM is a fail. While we don't know whether the call-in ASM will be a pass or a fail, we do know the probability that it will be a fail based on ASM failure probability calculated for the time of the call-in ASM. Then, it is a simple matter to "blend" the individual failure probabilities for the case where the call-in ASM is a pass and where it is a fail to arrive at the 24 monthly failure probabilities after the call-in ASM:

$$\begin{aligned} &Fprob_{afterCIA} \qquad \text{[Equation 4-1]} \\ &= (Fprob_{afterCIA} \mid \text{assuming CIA = Pass}) \bullet (1-Fprob_{CIA}) \\ &\quad + (Fprob_{afterCIA} \mid \text{assuming CIA = Fail}) \bullet Fprob_{CIA} \end{aligned}$$

where: $Fprob_{CIA}$ is the probability that the vehicle will fail the call-in ASM.

CIA denotes the Call-In ASM.

The idea of blending probabilities is also applied in the time domain. For any given vehicle, we do not know when the vehicle will come to an I/M inspection station for its next test. However, we do know the probability that it will come in any given month. This is given by the ΔCprobs. Therefore, to make a forecast of future ASM failure probabilities or future FTP mass emissions, we multiply the calculated failure probability time series or estimated FTP mass emission time series assuming that the vehicle comes back in a particular month by the probability that the vehicle will come back in that month. Then, the sum of those weighted time series is calculated to arrive at the failure probability time profile or FTP mass emissions time profile that is expected based on the probabilities that the vehicle will next get inspected in each given month. These weighting probabilities, which are the ΔCprobs described earlier, are key to the forecasting calculations.

The remainder of this subsection will describe the detailed calculations for forecasting for a particular vehicle in the pilot dataset. This is for VIN = 1FABP50U7JG198918. This 1988 Ford Taurus had an RSD measurement on November 22, 2004. The vehicle's previous-cycle initial-test was performed on February 15, 2003 in which it failed the ASM 2525 NX and passed the other five mode/pollutant tests. The vehicle was repaired on February 19, 2003, passed all mode/pollutant tests, and was certified. Because the vehicle received an RSD measurement in November 2004, that vehicle is "brought to our attention" at that time. In the field situation, I/M program staff would want to decide what should be done with that vehicle. Should it be called-in for a call-in ASM or for a scrappage ASM? Since the vehicle would be expected to get its next biennial inspection in February 2005, which is just four months away, should the vehicle be directed to a high-performing station or exempted? Or should the vehicle owner not be contacted so that the vehicle continues without intervention in the Normal I/M Process? All of these questions can be asked of any vehicle at any time – even if an RSD measurement has not been made – since we have ASM failure prediction models with and without RSD measurements as inputs.

To begin to work toward the answers to these questions, we will consider in detail the ASM failure probabilities and estimated FTP mass emissions for the case if the vehicle would get its next-cycle initial-test four months after the decision point. In this case the decision point is the date of the RSD measurement. Although we will not show them, analogous calculations must also be made for 47 other cases where the vehicle comes back in the first month after decision date, in the second month after the decision date, in the third month after the decision date, and all the way up to the forty-eighth month after the decision date. The results of all these 48 different calculations are then blended with the appropriate (brown or pink) ΔCprobs to arrive at the forecasted overall monthly ASM failure probability and FTP mass emissions for this specific vehicle for 24 months into the future.

Failed Miles Driven for the Normal I/M Process – The case for the Normal I/M Process when the vehicle returns in the fourth month after the decision date for its AFD is shown in Table 4-2. Column A shows the month of the AFD, which is the month that the vehicle is assumed to get its next-cycle initial test. For this example, it is Month 4. Column B shows the number of months since the decision date. The RSD and, therefore, the decision date is represented by the solid black line at the top of the table just above Month 0. The AFD is assumed to occur in the solid black line in the table just above Month 4. The table makes calculations up to 48 months since the decision date. The month since decision date values are "floored." For example, Month 0 represents the first 30 days after the decision date. Column C shows the number of days after the AFD for the purposes of calculating ASM failure probabilities using the models.

Columns D and E show the overall ASM failure probabilities for this vehicle for two cases: for the case if the AFD, which is in Month 4, is a pass, and for the case if the AFD is a fail and the vehicle is repaired. Of course, since the AFD is in the future, we do not know whether the AFD will be a pass or fail. Accordingly, as described above, we need to blend the probabilities calculated in Columns D and E for Months 4 to 48. What should the blending value be?

Table 4-2. Sample Forecast Calculations for Normal I/M Process

A	B	C	D	E	F	G	H	I	J	K	L
Month of AFD	Months since Decision Date	Days after AFD	Fprob after AFD (if AFD is Pass)	Fprob after AFD (if AFD is Fail/ Repair)	(purple) Fprob after Previous-Cycle ASM	Blending Value (purple Fprob in Month of AFD)	Fprob after AFD (Blended)	Fprob after Decision Date	ΔCprob (brown)	ΔCprob in Month of AFD	Partial Fprob for this AFD month
X	Y										
4	0				0.3410			0.3410	0.0367	0.2940	0.1003
4	1				0.3439			0.3439	0.0464	0.2940	0.1011
4	2				0.3467			0.3467	0.0788	0.2940	0.1019
4	3				0.3495			0.3495	0.1775	0.2940	0.1027
4	4	0.0	0.1922	0.2374	0.3522	0.3522	0.2081	0.2081	0.2940	0.2940	0.0612
4	5	30.4	0.1952	0.2406	0.3550	0.3522	0.2112	0.2112	0.1261	0.2940	0.0621
4	6	60.8	0.1982	0.2439	0.3577	0.3522	0.2143	0.2143	0.0644	0.2940	0.0630
4	7	91.3	0.2012	0.2471	0.3604	0.3522	0.2174	0.2174	0.0346	0.2940	0.0639
4	8	121.7	0.2043	0.2503	0.3631	0.3522	0.2205	0.2205	0.0238	0.2940	0.0648
4	9	152.1	0.2073	0.2535	0.3658	0.3522	0.2236	0.2236	0.0182	0.2940	0.0657
4	10	182.5	0.2104	0.2567	0.3684	0.3522	0.2267	0.2267	0.0145	0.2940	0.0666
4	11	212.9	0.2135	0.2600	0.3711	0.3522	0.2298	0.2298	0.0110	0.2940	0.0676
4	12	243.3	0.2166	0.2632	0.3737	0.3522	0.2330	0.2330	0.0085	0.2940	0.0685
.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.
4	47	1307.9	0.3248	0.3708	0.4439	0.3522	0.3410	0.3410	0.0000	0.2940	0.1002
4	48	1338.3	0.3277	0.3735	0.4452	0.3522	0.3438	0.3438	0.0000	0.2940	0.1011

AFD denotes ASM following Decision Point
CIA denotes Call-In ASM
ScA denotes Scrappage ASM

The blending value should be the probability that the vehicle will fail the AFD test. The vehicle has been driving since February 2003, which is 21 months before the decision point (Month 0) with the ASM failure probability increasing as described by the vehicle's overall ASM failure probability model. These calculated values, in this case using Model C, are shown in Column F. The Column F Fprobs are all calculated using the previous-cycle information as inputs. Clearly, the chances of the vehicle failing the AFD in Month 4 are 0.3522. Therefore, the value of 0.3522 should be used as the blending value as shown in Column G to blend the values from Column D and E using Equation 4-1. This produces the blended Fprob values in Column H for the failure probabilities for this vehicle after the AFD is administered. These probabilities take into account both the probability that the vehicle will fail the AFD and the future probabilities that the vehicle will fail another ASM test that could be given after the AFD.

But Column H is blank for Months 0 through 3 above the month of the AFD. What should these failure probabilities be? The answer is that these failure probabilities are just given by those in Column F for Months 0 to 3 since, during this period, the vehicle failure probabilities are still increasing based on the results of the previous-cycle ASM test that was given 21 months before the decision date. The results of the failure probabilities before the AFD for Months 0 to 3 in Column F and the results after the AFD for Months 4 to 48 in Column H are combined into Column I. This column gives the overall ASM failure probabilities for this vehicle given its VID history and assuming that the vehicle will receive its AFD in Month 4. An examination of the values shows that from Months 0 to 3 the overall ASM probability is slowly increasing. Then, in Month 4, when the vehicle receives its AFD the probability drops substantially and then begins to rise again toward Month 48. The drop in failure probability at the AFD is a consequence of the combined effects of the change in failure probabilities if the AFD is passed and the probability that the AFD will be failed.

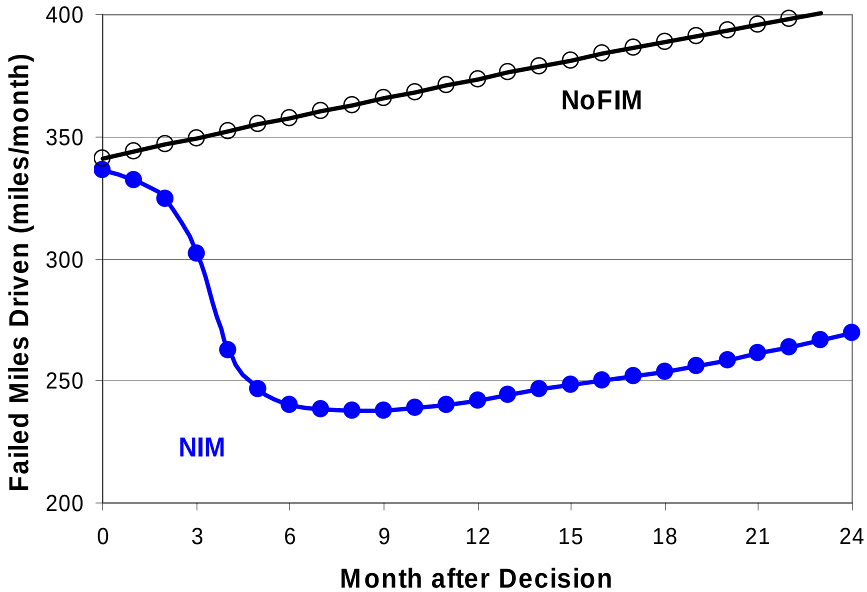
Table 4-2 represents just the probabilities that would be expected if the AFD occurred in Month 4. As described earlier, these same types of calculations need to be done separately for the 48 cases when the AFD is in each of the 48 months after the decision date. Then, the Fprobs after Decision Date in Column I need to be weighted by the appropriate ΔCprobs. For the Normal I/M Process, the appropriate ΔCprobs are the brown ΔCprobs. The brown ΔCprobs are based on cumulative I/M completion probabilities that begin at the previous-cycle certification date as described in Section 3.1. The ΔCprobs values also take into account the fact that the vehicle has not received a change in ownership inspection between February 2003, which is the previous-cycle date, and November 2004, which is the decision date. Column J shows the brown ΔCprobs for this situation, which are taken from Table 3-2.

Only one of these ΔCprob values is needed for weighting the Fprob after decision date values in Column I for AFD Month 4. This is the value that represents the probability that the vehicle will receive its next-cycle initial-test inspection four months after the decision date. This is given by the value 0.2940 which is in Column J and Month 4. This brown ΔCprob value fills all the cells in Column K and is used to multiply all the values in Column I to arrive at the Fprob contribution for the case when the AFD will occur in Month 4. The AFD Month 4 time series contribution is given in Column L for Months 0 to 48. Values like the values calculated in Column L are provided by all of the other 47 cases of AFD months. Then, all of the corresponding values from these 48 cases are summed for each Month Since Decision Date. When all of these values are added, the result is the time series for the expected failure probability of the vehicle for each month after the decision date taking into account the probability that the vehicle will receive its AFD in any given month after the decision date.

If we know from examination of VID history records or by assuming EMFAC mileage accumulation rates based on vehicle age that this particular vehicle drives 1,000 miles a month, then the number of miles that this vehicle drives in a failed status for each month is simply the product of the miles driven each month and the probability that the vehicle is in a failed status. The resulting time series curve for this vehicle for the Normal I/M Process is given in Figure 4-1 by the curve with the solid dots. The curve shows a large drop in failed miles driven in the vicinity of three and four months after the decision point which corresponds to about 24 months after the previous-cycle inspection. This is precisely the location that we expect failed miles driven to take a large drop since large numbers of vehicles return for their biennial inspection on their biennial anniversary.

This curve takes into account all of the inputs to Model C including the previous-cycle ASM mode/pollutant pass/fail results, the time that the AFD is after the previous-cycle test (even as the time changes through Table 4-2), vehicle aging (even as the age changes through Table 4-2), and all six ASM mode/pollutant cutpoints at the time of the AFD. Because the failure probability model used was specific to the vehicle description and model year of the vehicle, the results in Figure 4-1 for the Normal I/M Process also include the specific idiosyncrasies of the way in which individual ASM mode/pollutants in Ford Tauruses respond to repairs and degrade after repairs are made. Finally, the Normal I/M Process results shown in Figure 4-1 reflect the influence of when vehicle owners may return for their next I/M inspection including the effects of change of ownership tests.

Figure 4-1. Sample Forecast Failed Miles Driven for Normal I/M Process and for No Further I/M



The values in the table in failed miles driven can easily be converted to overall ASM failure probability by dividing the failed miles driven by 1,000 miles per month. Thus, the curve also shows that the overall ASM failure probability is expected to drop from about 0.34 in Month 0 to a minimum of about 0.24 in Month 8.

What would happen to this vehicle if the owner decided to no longer participate in the I/M program and did not perform any repairs on his vehicle in the future? This is given by the curve in Figure 4-1 with the open circles and is obtained by plotting the values from Column F of Table 4-2. The difference between the two curves in Figure 4-1 therefore, is a measure of the benefit of the I/M program to this vehicle for this period of time. With further development, this approach can be used to create a new method for evaluating I/M programs.

Since the failed miles driven calculated for the Normal I/M Process curve and for the No Further I/M curve are based on the Fprob models, and since the Fprob models were developed using VID data from all types of California I/M stations, the NIM and NoFIM curves in Figure 4-1 represent the vehicle's forecasted failed miles driven on the basis of an average California I/M station.

Failed Miles Driven for Directing/Exempting - Directing and Exempting share a common failed miles driven curve. However, the curve is used differently and has a different meaning for the two questions. In the case of Exempting, the Directing/Exempting (DX) curve represents the expected failed miles driven in the 24 months after the decision for exempting a vehicle. During exempting a vehicle is given a new certification at Month 0, but it is not required to visit an I/M station for an inspection. Thus, the ASM failure probabilities for an exempted vehicle continue on the same path that they had been on since the vehicle's previous-cycle certification. Because of this, the calculations for the Fprob after the decision date for Exempting as shown in Table 4-3 Columns A through I are exactly the same values as those used for the Normal I/M Process as shown in Table 4-2 in Columns A through I. The difference between Exempting and the Normal I/M Process is that because, for Exempting, the vehicle is given a new certification in Month 0, the vehicle will follow a different next-cycle set of probabilities that reflect the new certification. These new probabilities are the pink ΔCprobs as described in Section 3.1. For the example problem, shown in Table 4-3, the pink ΔCprobs are taken from Table 3-1. The only difference between the calculations for the Normal I/M Process and Exempting is the use of the pink ΔCprobs instead of the brown ΔCprobs.

After summing the partial Fprobs in Column L across all 48 AFD Months and multiplying by 1,000 miles per month, Figure 4-2 is produced for the estimated failed miles driven for Directing/Exempting. The curve starts in Month 0 at approximately the same 340 miles per month as the Normal I/M Process curve in Figure 4-1. However, instead of dropping rapidly around Month 4, the Directing/Exempting curve stays high and drops rapidly 24 months after the decision. This delay in the decrease in failed miles driven for Directing/Exempting is a consequence of giving the vehicle a new certification at Month 0. The failed miles driven curve staying high during the 24-month period is a consequence of the fact that no ASM inspection was conducted at the time of the decision in Month 0.

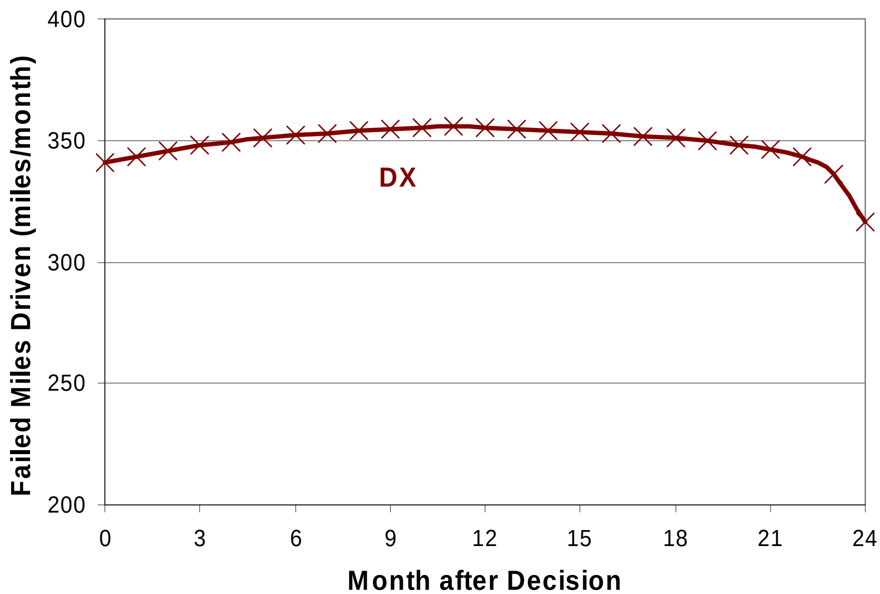
The Directing/Exempting curve is also used for Directing. In this case, the curve represents the worst case scenario for a vehicle that gets a fraudulent inspection in Month 0. The worst case example of a fraudulent inspection is one in which the inspector merely gives the vehicle a new certification and performs no testing and no repairs. Use of the DX curve for ranking vehicles for Exempting and Directing is discussed further in Section 4.3.

Table 4-3. Sample Forecast Calculations for Directing/Exempting

A	B	C	D	E	F	G	H	I	J	K	L
Month of AFD X	Months since Decision Date Y	Days after AFD	Fprob after AFD (if AFD is Pass)	Fprob after AFD (if AFD is Fail/ Repair)	(purple) Fprob after Previous-Cycle ASM	Blending Value (Purple Fprob in Month of AFD)	Fprob after AFD (Blended)	Fprob after Decision Date	ΔCprob (pink)	ΔCprob in Month of AFD	Partial Fprob for this AFD month
4	0				0.3410			0.3410	0.0014	0.0081	0.0028
4	1				0.3439			0.3439	0.0026	0.0081	0.0028
4	2				0.3467			0.3467	0.0026	0.0081	0.0028
4	3				0.3495			0.3495	0.0047	0.0081	0.0028
4	4	0.0	0.1922	0.2374	0.3522	0.3522	0.2081	0.2081	0.0081	0.0081	0.0017
4	5	30.4	0.1952	0.2406	0.3550	0.3522	0.2112	0.2112	0.0099	0.0081	0.0017
4	6	60.8	0.1982	0.2439	0.3577	0.3522	0.2143	0.2143	0.0106	0.0081	0.0017
4	7	91.3	0.2012	0.2471	0.3604	0.3522	0.2174	0.2174	0.0113	0.0081	0.0018
4	8	121.7	0.2043	0.2503	0.3631	0.3522	0.2205	0.2205	0.0117	0.0081	0.0018
4	9	152.1	0.2073	0.2535	0.3658	0.3522	0.2236	0.2236	0.0121	0.0081	0.0018
4	10	182.5	0.2104	0.2567	0.3684	0.3522	0.2267	0.2267	0.0136	0.0081	0.0018
4	11	212.9	0.2135	0.2600	0.3711	0.3522	0.2298	0.2298	0.0143	0.0081	0.0019
4	12	243.3	0.2166	0.2632	0.3737	0.3522	0.2330	0.2330	0.0189	0.0081	0.0019
.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.
4	47	1307.9	0.3248	0.3708	0.4439	0.3522	0.3410	0.3410	0.0000	0.0081	0.0028
4	48	1338.3	0.3277	0.3735	0.4452	0.3522	0.3438	0.3438	0.0000	0.0081	0.0028

AFD denotes ASM following Decision Point
CIA denotes Call-In ASM
ScA denotes Scrappage ASM

Figure 4-2. Sample Forecast Failed Miles Driven for Directing/Exempting



Failed Miles Driven for Calling-In No-Sticker - For the case of calling in a vehicle for a call-in ASM test in the decision month, the calculations become more complicated because the results of the call-in ASM test need to be considered. However, the same basic tools that were used for the Normal I/M Process and for Directing/Exempting are used.

The sample calculations for the same vehicle and for an AFD that occurs in the fourth month after the decision date are shown in Table 4-4. Columns A, B, and C are the same as the previous tables. Unlike the Normal I/M Process and Directing/Exempting, for Calling-In a special call-in ASM test is performed at the time of the bold line in the table just above Month 0. In addition, the AFD test occurs at the bold line above Month 4. The effects of both of these ASM tests need to be taken into account. Columns D and E in Table 4-4 give the failure probabilities of the vehicle if the call-in ASM is a pass (Column D) and if the call-in ASM is a fail and a repair is made (Column E). The values in those columns show that as the month increases, the values of the failure probabilities increase. However, the failure probabilities for Column E, where the call-in ASM was a fail, are always higher than those for Column D, where the call-in ASM was a pass.

Next, we consider the failure probabilities for the two cases when the AFD is a pass or a fail/repair. These probabilities are shown for Months 4 to 48 in Columns F and G. They are calculated based on the corresponding assumptions for fail and pass for the AFD test which would occur for this table in Month 4.

Table 4-4. Sample Forecast Calculations for Calling-In No-Sticker

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
Month of AFD	Months since Decision Date	Days after AFD	(light-green) Fprob after CIA (if CIA is Pass)	(light-blue) Fprob after CIA (if CIA is Fail/ Repair)	Fprob after AFD (if AFD is Pass)	Fprob after AFD (if AFD is Fail/ Repair)	Blending Value (light-green) Fprob in Month of AFD	Blending Value (light-blue) Fprob in Month of AFD	Fprob after Passing Call-In ASM, then after the AFD	Fprob after Failing Call-In ASM, then after the AFD	Fprob (purple) after Previous-Cycle ASM	Blending Value (purple) Fprob at time of Call-In ASM	Fprob after Decision Date	ΔCprob (brown)	ΔCprob in Month of AFD	Partial Fprob for this AFD month
X	Y															
4	0		0.1902	0.2362					0.1902	0.2362	0.3410	0.3410	0.2059	0.0367	0.2940	0.0605
4	1		0.1932	0.2395					0.1932	0.2395	0.3439	0.3410	0.2090	0.0464	0.2940	0.0614
4	2		0.1963	0.2427					0.1963	0.2427	0.3467	0.3410	0.2121	0.0788	0.2940	0.0623
4	3		0.1993	0.2460					0.1993	0.2460	0.3495	0.3410	0.2152	0.1775	0.2940	0.0633
4	4	0.0	0.2023	0.2492	0.1922	0.2374	0.2023	0.2492	0.2014	0.2035	0.3522	0.3410	0.2021	0.2940	0.2940	0.0594
4	5	30.4	0.2054	0.2525	0.1952	0.2406	0.2023	0.2492	0.2044	0.2065	0.3550	0.3410	0.2051	0.1261	0.2940	0.0603
4	6	60.8	0.2084	0.2557	0.1982	0.2439	0.2023	0.2492	0.2075	0.2096	0.3577	0.3410	0.2082	0.0644	0.2940	0.0612
4	7	91.3	0.2115	0.2590	0.2012	0.2471	0.2023	0.2492	0.2105	0.2127	0.3604	0.3410	0.2113	0.0346	0.2940	0.0621
4	8	121.7	0.2146	0.2622	0.2043	0.2503	0.2023	0.2492	0.2136	0.2157	0.3631	0.3410	0.2143	0.0238	0.2940	0.0630
4	9	152.1	0.2177	0.2655	0.2073	0.2535	0.2023	0.2492	0.2167	0.2188	0.3658	0.3410	0.2174	0.0182	0.2940	0.0639
4	10	182.5	0.2208	0.2687	0.2104	0.2567	0.2023	0.2492	0.2198	0.2219	0.3684	0.3410	0.2205	0.0145	0.2940	0.0648
4	11	212.9	0.2239	0.2720	0.2135	0.2600	0.2023	0.2492	0.2229	0.2251	0.3711	0.3410	0.2236	0.0110	0.2940	0.0657
4	12	243.3	0.2270	0.2752	0.2166	0.2632	0.2023	0.2492	0.2260	0.2282	0.3737	0.3410	0.2267	0.0085	0.2940	0.0666
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
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.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
4	47	1307.9	0.3349	0.3818	0.3248	0.3708	0.2023	0.2492	0.3341	0.3362	0.4439	0.3410	0.3348	0.0000	0.2940	0.0984
4	48	1338.3	0.3378	0.3845	0.3277	0.3735	0.2023	0.2492	0.3370	0.3391	0.4452	0.3410	0.3377	0.0000	0.2940	0.0993

AFD denotes ASM following Decision Point
CIA denotes Call-In ASM
ScA denotes Scrappage ASM

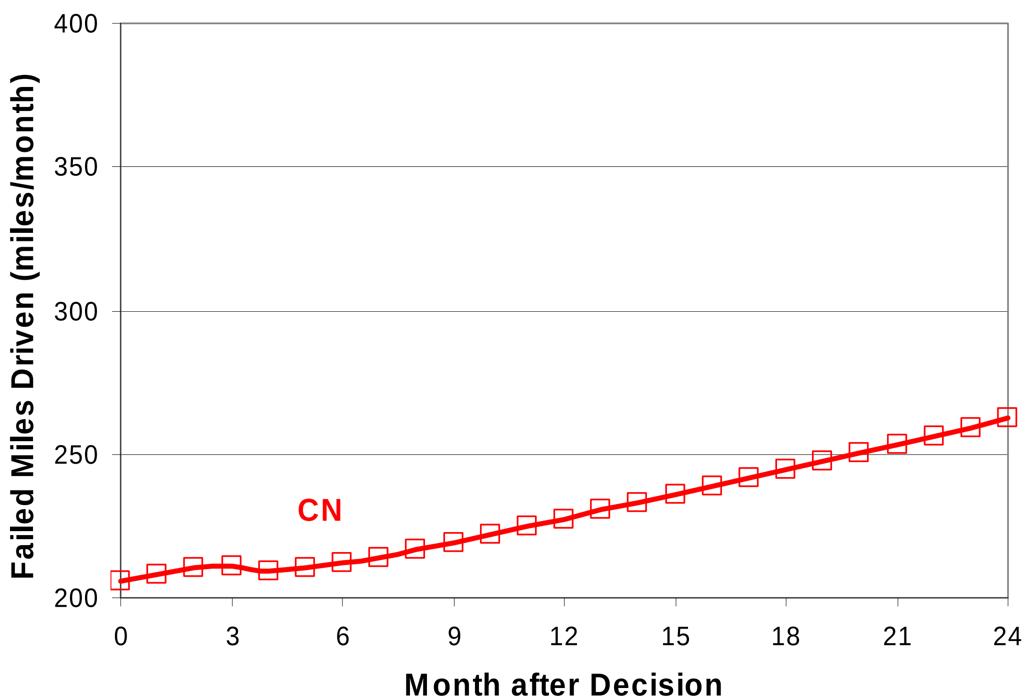
Now, we need to calculate the joint probabilities for passing or failing the call-in ASM and then passing or failing the AFD. First, we consider the case if the call-in ASM is passed. The results are shown in Column J. If the call-in ASM is passed, then the probability of failing a subsequent ASM test during Month 0 through Month 3 is given by the failure probabilities in Column D for Month 0 through 3. Therefore, these values are placed in Column J. Next, we need to calculate the failure probability of an ASM test given after the AFD test. This is calculated by blending the values in Columns F and G for Months 4 to 48 using the blending value that is the probability that the AFD will fail in Month 4. This blending value is given in Column D at Month 4 and has a value of 0.2023. This blending value occupies all of the cells in Column H for Months 4 to 48. By applying this blending value in Column H to the Fprobs for AFD passing in Column F and for AFD failing in Column G using Equation 4-1, the values in Column J from Month 4 to 48 are produced. The resulting values in Column J are then the ASM overall failing probability if the call-in ASM is a pass and taking into account the failure probabilities for the AFD. The values in Column J show that the failure probability increases slowly from Month 0 to 3 and than takes a decrease in the rate of increase at the time of the AFD in Month 4 and then increases thereafter.

The same sorts of calculations are used to calculate Column K which is the failure probability after failing the call-in ASM. In this case, the failure probabilities between the decision date and the AFD are taken from Column E for Months 0 to 3 and the values for the remainder of Column K are produced by blending the failure probabilities from Column F and G using the blending value of 0.2492 which is the failure probability in Month 4 if the call-in ASM was a fail. Inspection of Columns K and J shows that the failure probabilities after failing the call-in ASM are slightly higher than those after passing the call-in ASM.

At this point, however, the problem still is not completely solved because we don't know if the vehicle will pass or fail the call-in ASM since that test is still in the future. The solution to this question is again solved with blending the probabilities found in Columns J and K using the blending value which is the failure probability of the call-in ASM test. Column L gives the overall ASM failure probability for the vehicle based on the previous-cycle I/M results 21 months before the decision date using Model C. The appropriate blending value is the failure probability of 0.3410 for Month 0 in Column L. This value fills all cells in Column M to indicate that it is used for blending all cells in J and K using the blending Equation 4-1. This final blending produces the failure probabilities given in Column N. These failure probabilities are for all months since the decision date when the AFD is in Month 4. They include the effects of passing and failing the call-in ASM and the effects of passing and failing the AFD.

The failure probability results for AFD Month 4 that are given in Column N need to be combined with all of the other AFD Months to arrive at the expected failed miles driven for Calling-In No-Sticker. The same approach is used as for the Normal I/M Process calculations in Table 4-2. The brown ΔCprobs are shown in Column O of Table 4-4. The appropriate blending value for the ΔCprobs is 0.2940 for Month 4 in Column O. This value is repeated for all rows in Column P to show that all values in Column N are multiplied by this value to produce the partial Fprobs in Column Q. When the partial Fprobs from corresponding Months Since Decision Date are added for all AFD Months time series and the results are multiplied by the monthly miles driven of 1,000 miles per month, the failed miles driven plot shown in Figure 4-3 for Calling-In No-Sticker is the result. This plot shows a more or less monotonic increase in failed miles driven as month after decision increases. The only deviation from monotonicity is the slight inflection point at four months.

Figure 4-3. Sample Forecast Failed Miles Driven for Calling-In No-Sticker



Failed Miles Driven for Calling-In Sticker - The other Calling-In case that we have calculated in this study is the case where if a vehicle is called in it is given a new 24-month certification for meeting the requirements of the call-in ASM.

The calculations for failed miles driven for Calling-In Sticker are shown in Table 4-5. The values for Columns A through N are exactly the same as for the calculations of Calling-In

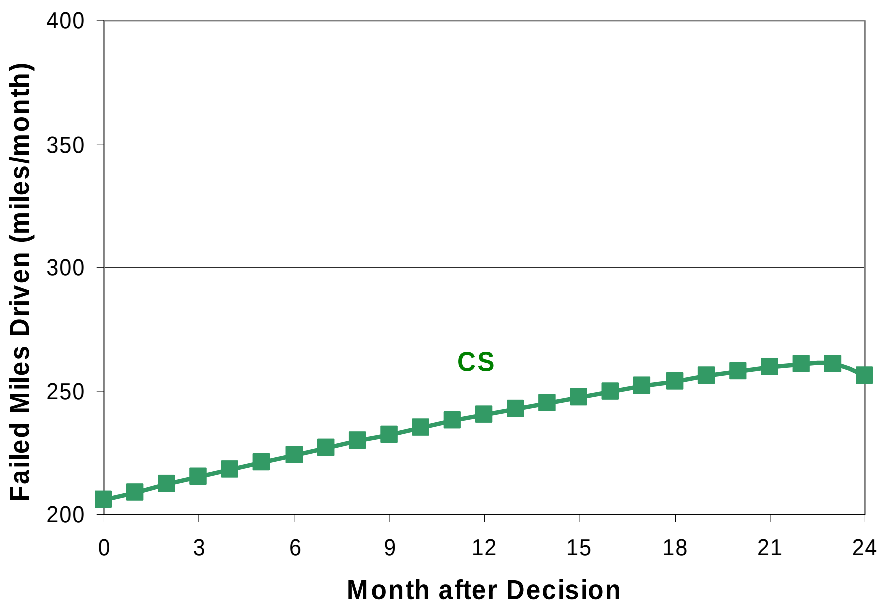
Table 4-5. Sample Forecast Calculations for Calling-In Sticker

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
Month of AFD X	Months since Decision Date Y	Days after AFD	(light-green) Fprob after CIA (if CIA is Pass)	(light-blue) Fprob after CIA (if CIA is Fail/ Repair)	Fprob after AFD (if AFD is Pass)	Fprob after AFD (if AFD is Fail/ Repair)	Blending Value (light-green) Fprob in Month of AFD	Blending Value (light-blue) Fprob in Month of AFD	Fprob after Passing Call-In ASM, then after the AFD	Fprob after Failing Call-In ASM, then after the AFD	Fprob (purple) after Previous-Cycle ASM	Blending Value (purple) Fprob at time of Call-In ASM	Fprob after Decision Date	ΔCprob (pink)	ΔCprob in Month of AFD	Partial Fprob for this AFD month
4	0		0.1902	0.2362					0.1902	0.2362	0.3410	0.3410	0.2059	0.0014	0.0081	0.0017
4	1		0.1932	0.2395					0.1932	0.2395	0.3439	0.3410	0.2090	0.0026	0.0081	0.0017
4	2		0.1963	0.2427					0.1963	0.2427	0.3467	0.3410	0.2121	0.0026	0.0081	0.0017
4	3		0.1993	0.2460					0.1993	0.2460	0.3495	0.3410	0.2152	0.0047	0.0081	0.0017
4	4	0.0	0.2023	0.2492	0.1922	0.2374	0.2023	0.2492	0.2014	0.2035	0.3522	0.3410	0.2021	0.0081	0.0081	0.0016
4	5	30.4	0.2054	0.2525	0.1952	0.2406	0.2023	0.2492	0.2044	0.2065	0.3550	0.3410	0.2051	0.0099	0.0081	0.0017
4	6	60.8	0.2084	0.2557	0.1982	0.2439	0.2023	0.2492	0.2075	0.2096	0.3577	0.3410	0.2082	0.0106	0.0081	0.0017
4	7	91.3	0.2115	0.2590	0.2012	0.2471	0.2023	0.2492	0.2105	0.2127	0.3604	0.3410	0.2113	0.0113	0.0081	0.0017
4	8	121.7	0.2146	0.2622	0.2043	0.2503	0.2023	0.2492	0.2136	0.2157	0.3631	0.3410	0.2143	0.0117	0.0081	0.0017
4	9	152.1	0.2177	0.2655	0.2073	0.2535	0.2023	0.2492	0.2167	0.2188	0.3658	0.3410	0.2174	0.0121	0.0081	0.0018
4	10	182.5	0.2208	0.2687	0.2104	0.2567	0.2023	0.2492	0.2198	0.2219	0.3684	0.3410	0.2205	0.0136	0.0081	0.0018
4	11	212.9	0.2239	0.2720	0.2135	0.2600	0.2023	0.2492	0.2229	0.2251	0.3711	0.3410	0.2236	0.0143	0.0081	0.0018
4	12	243.3	0.2270	0.2752	0.2166	0.2632	0.2023	0.2492	0.2260	0.2282	0.3737	0.3410	0.2267	0.0189	0.0081	0.0018
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
4	47	1307.9	0.3349	0.3818	0.3248	0.3708	0.2023	0.2492	0.3341	0.3362	0.4439	0.3410	0.3348	0.0000	0.0081	0.0027
4	48	1338.3	0.3378	0.3845	0.3277	0.3735	0.2023	0.2492	0.3370	0.3391	0.4452	0.3410	0.3377	0.0000	0.0081	0.0027

AFD denotes ASM following Decision Point
CIA denotes Call-In ASM
ScA denotes Scrappage ASM

No-Sticker in Table 4-4 for Columns A through N. The only difference in the calculations for No-Sticker and Sticker is the use of the pink ΔCprobs in Columns O and P. Just as for the use of the same pink ΔCprobs in Table 4-3 for Directing/Exempting, the pink ΔCprobs in Table 4-5 reflect the plan to give a new 24-month certification at the completion of the call-in ASM. Using the pink ΔCprobs for Calling-In Sticker instead of the brown ΔCprobs for Calling-In No-Sticker causes the time series for the different AFD Months to be combined in a different way. This produces the failed miles driven plot for Calling-In Sticker in Figure 4-4. That figure shows a generally monotonically increasing trend for failed miles driven that is very similar to the one for Calling-In No-Sticker. The difference is that the inflection point is at 24 months after Month 0. This reflects the biennial anniversary of the new certification given in Month 0 for the Calling-In Sticker option.

Figure 4-4. Sample Forecast Failed Miles Driven for Calling-In Sticker



FTP Mass Emissions for the Normal I/M Process – As a baseline for estimating the FTP mass emissions benefits of different intervention activities, we need to calculate the FTP mass emissions that are emitted by each vehicle over the 24 months after the decision point in the Normal I/M Process. The calculations are shown for AFD Month 4 in Table 4-6. The calculation for estimated FTP emissions for the Normal I/M Process is very similar to the calculation of failure probabilities for the Normal I/M Process that was shown in Table 4-2. The main difference is that instead of blending failure probabilities, Table 4-6 blends FTP emission

Table 4-6. Sample Forecast Calculations for Normal I/M Process FTP Emissions

A	B	C	D	E	F	G	H	I	J	K	L	M
Month of AFD	Months since Decision Date	Days after AFD	FTP NX (g/mile) emissions after Previous-Cycle IM Test	FTP NX (g/mile) after AFD (if AFD is Pass)	FTP NX (g/mile) after AFD (if AFD is Fail/ Repair)	(purple) Fprob after Previous-Cycle ASM	Blending Value (purple Fprob in Month of AFD)	FTP NX (g/mile) after AFD (Blended)	FTP NX (g/mile) after Decision Date	ΔCprob (brown)	ΔCprob in Month of AFD	Partial FTP NX (g/mile) for this AFD month
X	Y											
4	0		1.51			0.3410			1.51	0.0367	0.2940	0.44
4	1		1.52			0.3439			1.52	0.0464	0.2940	0.45
4	2		1.53			0.3467			1.53	0.0788	0.2940	0.45
4	3		1.54			0.3495			1.54	0.1775	0.2940	0.45
4	4	0.0	1.55	1.15	1.29	0.3522	0.3522	1.20	1.20	0.2940	0.2940	0.35
4	5	30.4	1.56	1.16	1.29	0.3550	0.3522	1.21	1.21	0.1261	0.2940	0.35
4	6	60.8	1.57	1.17	1.31	0.3577	0.3522	1.21	1.21	0.0644	0.2940	0.36
4	7	91.3	1.58	1.17	1.32	0.3604	0.3522	1.22	1.22	0.0346	0.2940	0.36
4	8	121.7	1.59	1.18	1.33	0.3631	0.3522	1.23	1.23	0.0238	0.2940	0.36
4	9	152.1	1.60	1.18	1.34	0.3658	0.3522	1.24	1.24	0.0182	0.2940	0.36
4	10	182.5	1.60	1.19	1.35	0.3684	0.3522	1.25	1.25	0.0145	0.2940	0.37
4	11	212.9	1.61	1.20	1.36	0.3711	0.3522	1.25	1.25	0.0110	0.2940	0.37
4	12	243.3	1.62	1.20	1.37	0.3737	0.3522	1.26	1.26	0.0085	0.2940	0.37
.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.	.	.	.	.
4	47	1307.9	1.97	1.45	1.79	0.4439	0.3522	1.57	1.57	0.0000	0.2940	0.46
4	48	1338.3	1.98	1.46	1.81	0.4452	0.3522	1.58	1.58	0.0000	0.2940	0.47

AFD denotes ASM following Decision Point
CIA denotes Call-In ASM
ScA denotes Scrappage ASM

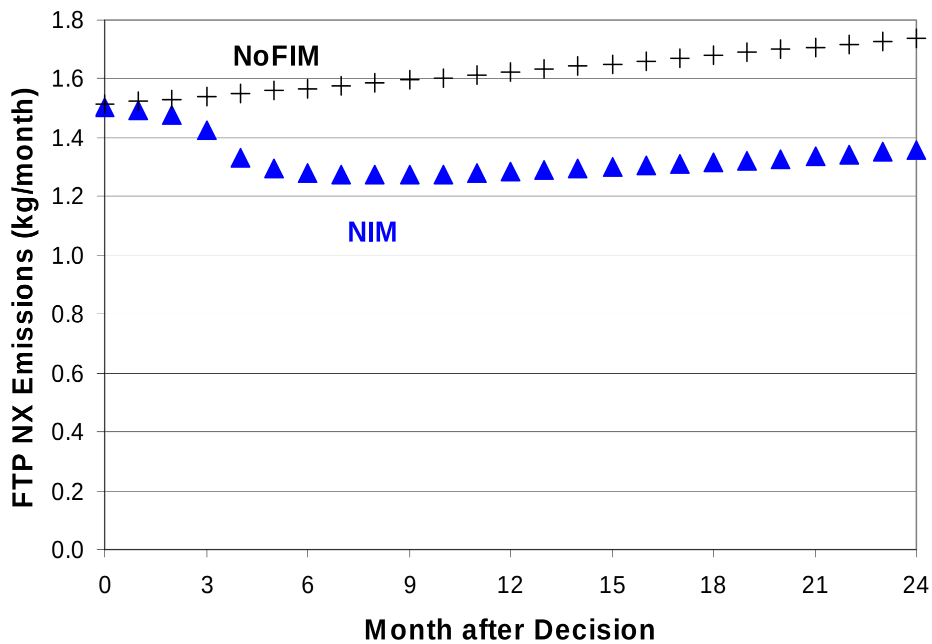
rates. For the purposes of ranking, separate calculations and separate ranking variables are made for the separate FTP pollutants. Table 4-6 shows the calculation for estimated FTP NX emissions.

Column D gives the estimated FTP NX emission rates based on the previous-cycle I/M test which was 21 months before Month 0. These would be the emission rates if there would be no ASM test of any kind since the previous-cycle I/M test. Columns E and F give the estimated FTP emission rates after an AFD test given in Month 4, respectively, for the cases where the AFD is a pass and the AFD is a fail. Note that the estimated FTP emission rates for the failing case in Column F are higher than for the passing case in Column E even though the vehicle that failed the AFD in Column F was repaired. Since we don't know whether the vehicle will pass or fail the AFD test in Month 4, we need to blend the estimated FTP NX emission rates for Columns E and F by the probability that the vehicle will fail the AFD test. This is given by the value of 0.3522 in Column G for Month 4. The blended values of the estimated FTP NX emission rates are given in Column I for Months 4 to 48 and were calculated using Equation 4-1.

For the four months before the AFD, the expected FTP emission rates are those in Column D for Months 0 through 3, which are based on the previous-cycle I/M test results. These emission rates are carried to Column J and the emission rates that were blended for Months 4 through 48 from Column I are also carried to Column J. This results in Column J having the expected FTP NX emission rates for the entire period after the decision date. Examination of the values in Column J show that the estimated FTP NX emission rates increase gradually during Months 0 to 3 and then drop in Month 4 as a result of the AFD test. After that period the FTP NX emission rates gradually increase again.

At this point, just as for the Normal I/M Process failed miles driven calculations in Table 4-2, the FTP emission rates in Column J are multiplied by the brown ΔCprob for Month 4, which has a value of 0.2940, to produce Column M, which is the partial FTP NX emission rates for Month 4. When all the partial emission rates for all 48 AFD Months are added together by Month Since Decision Date and then each value is multiplied by the 1,000 miles driven per month by this vehicle, the plot in Figure 4-5 is the result. This plot shows the estimated FTP NX emissions in the solid triangles in kg/month for the vehicle as it participates in the I/M process. The upper curve on the plot with the plus signs represents the estimated FTP NX emissions of this vehicle if it did not participate in the I/M program after Month 0. These values were obtained from Column D in Table 4-6.

Figure 4-5. Sample Forecast FTP Mass Emissions for Normal I/M Process



FTP Mass Emissions for Scrapping – To be able to rank vehicles for Scrapping, the estimated FTP mass emissions of the vehicle, if it is scrapped, also need to be calculated. At first the reader might think that this answer should be 0 grams per mile. However, the calculations need to take into account the possibility that a vehicle that is called-in for a scrappage ASM test may pass the test and, therefore, would not be given a scrappage offer.

Table 4-7 shows the Scrapping calculations for the estimated FTP NX emission rates calculated for the same vehicle in AFD Month 4. These calculations are very similar to those used for Calling-In No-Sticker in Table 4-4. The table begins with Columns D and E with the estimated FTP NX emission rates for the situation where the scrappage ASM result is a pass and fail, respectively. Clearly, if the scrappage ASM is a fail, the owner would be offered the scrappage option and, therefore, the FTP NX emission rates listed in Column E are 0 grams/mile. Columns F and G give the estimated FTP NX emission rates for Months 4 to 48 for the situations where the vehicle passes and fails the AFD in Month 4. Then, the estimated FTP NX emission rates after the AFD from Columns F and G are blended using the failure probability value of 0.2023 from Month 4 in Column H. This produces the estimated FTP NX emission rates for Month 4 to 48 in Column J for the period of time after the AFD if the vehicle passes the scrappage ASM test in Month 0. The estimated FTP NX emission rates in Column J for the period after the scrappage ASM in Month 0 and before the AFD in Month 4 for the situation where the scrappage ASM is a pass are taken from Column D and Months 0 to 3.

Table 4-7. Sample Forecast Calculations for Scrapping FTP Emissions

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q
Month of AFD	Months since Decision Date	Days after AFD	FTP NX (g/mile) after ScA (if ScA is Pass)	FTP NX (g/mile) after ScA (if ScA is Fail)	FTP NX (g/mile) after AFD (if AFD is Pass)	FTP NX (g/mile) after AFD (if AFD is Fail/ Repair)	(light-green) Fprob after ScA (if ScA is Pass)	Blending Value (light-green) Fprob in Month of AFD	FTP NX (g/mile) after Passing ScA, then after the AFD	FTP NX (g/mile) after Failing ScA, then after the AFD	Fprob (purple) after Previous-Cycle ASM	Blending Value (purple) Fprob at time of Call-In ASM)	FTP NX (g/mile) after Decision Date	ΔCprob (brown)	ΔCprob in Month of AFD	Partial FTP NX (g/mile) for this AFD month
X	Y															
4	0		1.15	0.00			0.1902		1.15	0.00	0.3410	0.3410	0.7580	0.0367	0.2940	0.2228
4	1		1.16	0.00			0.1932		1.16	0.00	0.3439	0.3410	0.7622	0.0464	0.2940	0.2241
4	2		1.16	0.00			0.1963		1.16	0.00	0.3467	0.3410	0.7665	0.0788	0.2940	0.2253
4	3		1.17	0.00			0.1993		1.17	0.00	0.3495	0.3410	0.7707	0.1775	0.2940	0.2266
4	4	0.0	1.18	0.00	1.15	1.29	0.2023	0.2023	1.18	0.00	0.3522	0.3410	0.7770	0.2940	0.2940	0.2284
4	5	30.4	1.18	0.00	1.16	1.29	0.2054	0.2023	1.19	0.00	0.3550	0.3410	0.7817	0.1261	0.2940	0.2298
4	6	60.8	1.19	0.00	1.17	1.31	0.2084	0.2023	1.19	0.00	0.3577	0.3410	0.7864	0.0644	0.2940	0.2312
4	7	91.3	1.20	0.00	1.17	1.32	0.2115	0.2023	1.20	0.00	0.3604	0.3410	0.7911	0.0346	0.2940	0.2326
4	8	121.7	1.20	0.00	1.18	1.33	0.2146	0.2023	1.21	0.00	0.3631	0.3410	0.7959	0.0238	0.2940	0.2340
4	9	152.1	1.21	0.00	1.18	1.34	0.2177	0.2023	1.22	0.00	0.3658	0.3410	0.8007	0.0182	0.2940	0.2354
4	10	182.5	1.22	0.00	1.19	1.35	0.2208	0.2023	1.22	0.00	0.3684	0.3410	0.8056	0.0145	0.2940	0.2368
4	11	212.9	1.22	0.00	1.20	1.36	0.2239	0.2023	1.23	0.00	0.3711	0.3410	0.8104	0.0110	0.2940	0.2382
4	12	243.3	1.23	0.00	1.20	1.37	0.2270	0.2023	1.24	0.00	0.3737	0.3410	0.8153	0.0085	0.2940	0.2397
.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
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4	47	1307.9	1.48	0.00	1.45	1.79	0.3349	0.2023	1.52	0.00	0.4439	0.3410	1.0031	0.0000	0.2940	0.2949
4	48	1338.3	1.49	0.00	1.46	1.81	0.3378	0.2023	1.53	0.00	0.4452	0.3410	1.0089	0.0000	0.2940	0.2966

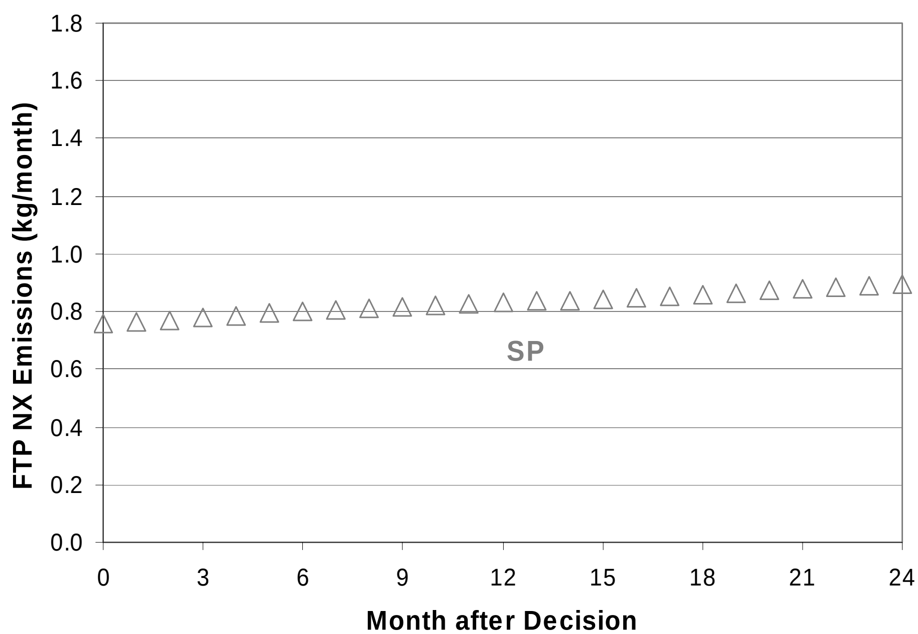
AFD denotes ASM following Decision Point
CIA denotes Call-In ASM
ScA denotes Scrappage ASM

The result is that Column J contains the expected FTP NX emission rates for every month after the scrappage ASM for the situation where the vehicle passes the scrappage ASM. In contrast, Column K gives the estimated FTP NX emission rates if the vehicle fails the scrappage ASM. These values are taken directly from Column E.

Since we do not know if the vehicle will pass or fail the scrappage ASM in Month 0, the estimated FTP NX emission rates from Columns J and K need to be blended by the probability that the vehicle will fail the scrappage ASM in Month 0. This blending value is 0.3410 and is obtained for Month 0 in Column L. The value is repeated for all cells in Column M. The blended FTP NX emission rates for all months after the decision date produced by the blending are given in Column N.

Finally, just as in Table 4-4 for Calling-In No-Sticker, the values in column N are multiplied by the appropriate brown ΔCprob value of 0.2940 for every month to arrive at the partial FTP NX emission rates for the AFD Month in Column Q. When the partial FTP NX emission rates for all 48 AFD Months are summed for each Month Since Decision Date and these values are multiplied by the 1,000 miles driven per month by this vehicle, the expected FTP NX mass emissions per month are the resulting quantities which are plotted in Figure 4-6.

Figure 4-6. Sample Forecast FTP Mass Emissions for Scrapping

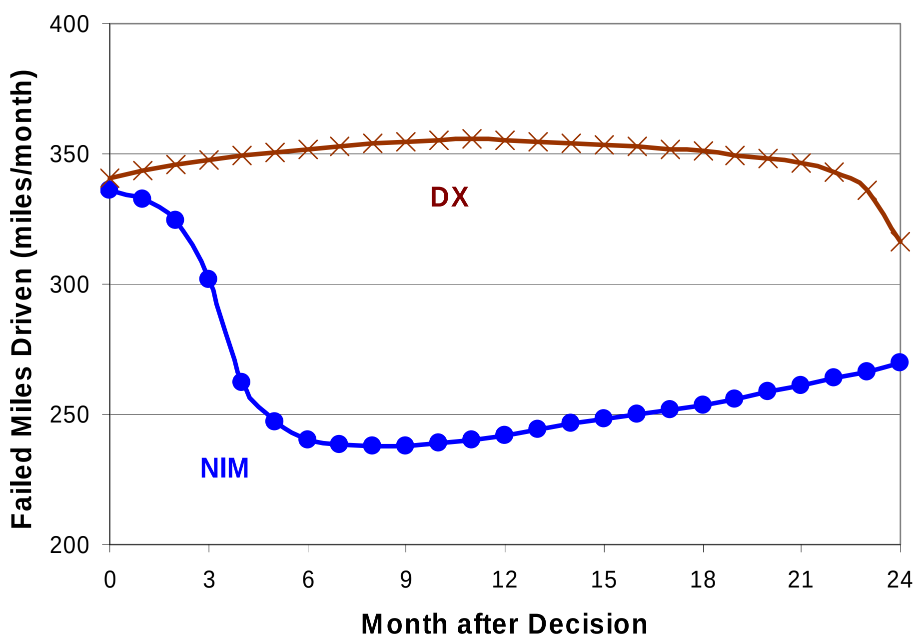


4.3 Calculating Ranking Variables for ΔFMD and ΔFTP/$

To rank vehicles for Directing, Exempting, Calling-In, and Scrapping, we need to convert the forecasted failed miles driven curves and the forecasted FTP mass emissions curves that were generated as described in Section 4.2 into single numerical quantities for ranking individual vehicles in the dataset. The quantity to be used for ranking Directing, Exempting, and Calling-In is ΔFMD, which is the change in failed miles driven over the 24 months following the decision point. For ranking vehicles for Scrapping, the quantity is ΔFTP/$, which is the estimated change in FTP mass emissions over 24 months after the decision point per dollar of vehicle value. First, we describe how these quantities are calculated and then we describe how they are ranked.

Directing and Exempting – The failed miles driven curves from Section 4.2 for the Normal I/M Process and for Directing/Exempting are overlaid in Figure 4-7. The figure shows that the normal I/M curve is below the Directing/Exempting curve throughout the 24-month period after the decision point.

Figure 4-7. Comparison of Forecasted Failed Miles Driven for Directing/Exempting and Normal I/M Process



Let us first think of the Directing/Exempting curve only in terms of Exempting. If the vehicle is exempted, then in Month 0 the vehicle is given a new certification. However, the vehicle has no chance for a repair induced by the I/M program and, in fact, the vehicle does not even come in to an I/M station. Accordingly, the distance that the Directing/Exempting curve is above the Normal I/M Process curve gives the increase in failed miles driven that is caused by exempting the vehicle. Therefore, the change in failed miles driven for Exempting is given by:

$$\Delta FMD_{Exempting} = FMD_{DX} - FMD_{NIM}$$

In terms of ranking the vehicles, we would want to exempt the vehicles that have their DX curves just barely above their NIM curves. Therefore, if we sort the vehicles in the dataset with the smallest values of $\Delta FMD_{Exempting}$ at the top, the top candidates for exemption will be at the top of the list.

Now consider Figure 4-7 from the Directing point of view. When vehicles are directed to high-performing stations,[28] the State is managing the risk of improper inspections on high-risk vehicles. Therefore, the basic fear is that all average-performing stations[29] might behave as the DX curve in Figure 4-7. That is, average-performing stations might merely give new certifications and might not do any repairs; while the assumption is that high-performing stations follow the NIM curve where vehicles are properly inspected and repaired. Therefore, Directing attempts to provide a change in failed miles driven estimated by:

$$\Delta FMD_{Directing} = FMD_{NIM} - FMD_{DX}$$

Because Directing is expected to produce a reduction in failed miles driven, ΔFMD should be a large negative number for the best Directing candidates. Accordingly, if $\Delta FMD_{Directing}$ is sorted from the lowest values to the highest values, the priority candidates for Directing will be at the top of the sort list.

To arrive at the total change in ΔFMD over 24 months, the individual differences for each month are simply added together. For the sample vehicle $\Delta FMD_{Exempting}$ = + 2167 miles and $\Delta FMD_{Directing}$ = -2167 miles over the 24 months after the decision. These values are the respective Exempting and Directing ranking values for this vehicle. Even though vehicles are ranked by these Directing values, the values themselves are not the benefits to be expected when

[28] High-performing station is a hypothetical category of California I/M inspection stations that would perform more-accurate I/M inspections and therefore would be able to provide greater emissions reductions than average-performing stations. In the analysis we did not attempt to determine which stations or which types of stations (Test Only, Test-and-Repair, Gold Shield, etc.) were average- or high-performing. Instead, based on station-performance information from BAR, subsequent reports will assume that the hypothetical high-performing stations have fail rates that are somewhat higher and after-repair emissions levels that are somewhat lower than those of average-performing stations.

[29] Average-performing station is a hypothetical category of California I/M inspection stations that have the average ASM inspection performance of all stations in the California I/M system (including Test-Only, Test-and-Repair, Gold-Shield, Referee, etc. stations), on all vehicles inspected, and for the study's historical VID data period for ASM inspections (July 1998 through April 2005) taken as a whole.

the vehicles are actually directed. The reason for this is that to calculate the ranking values for Directing, we assumed, as described above, that the regular I/M inspection was completely fraudulent (by using the DX curve) and that the inspection at the directed station was as accurate as an average-station inspection (by using the NIM) curve. These assumptions are extreme conditions for the real case. While these assumptions are fine for the purposes of ranking vehicles (since the assumption is introduced equally to all vehicles), for the purposes of calculating benefits, the failed miles driven and emissions results when using these assumptions must be modified so that they reflect the more realistic relative accuracies of high-performing and average-performing stations. This modification for calculation of benefits is described and performed in the subsequent implementation report.

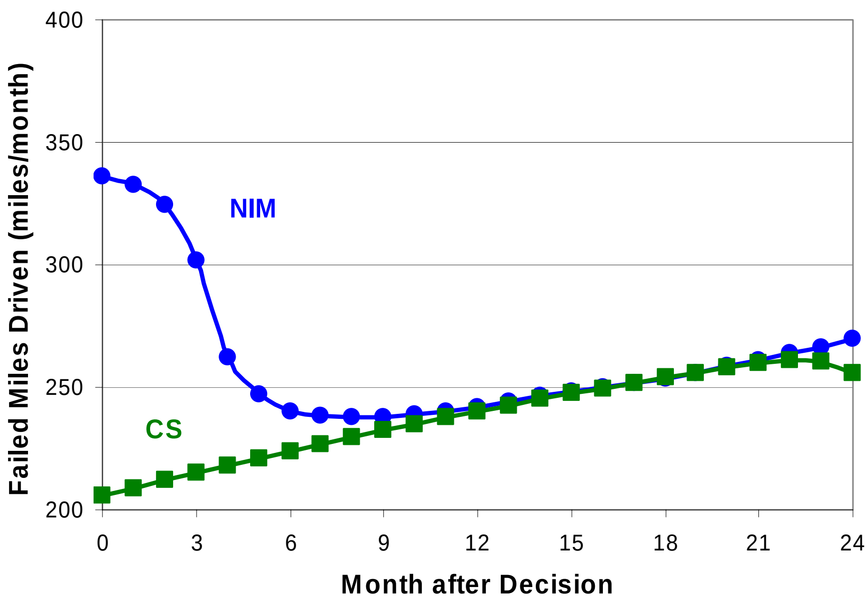
Calling-In Sticker – One possible Calling-In scenario is that vehicles would be called in, inspected, repaired if they failed, and then given a new certification at the time of the call-in ASM. Figure 4-8 shows the relevant curves to consider for this situation: the Normal I/M Process curve and the Calling-In Sticker curve. The CS curve begins at Month 0 below the NIM curve because the vehicle receives a call-in ASM test and possible repair in Month 0. Because the called-in vehicle is given a new certification in Month 0 as a result of this test, the inflection point in the CS curve is two-years later in Month 24 when that vehicle would be expected to come in for its next regular I/M inspection. The NIM curve gives the failed miles driven if the vehicle is not called in. In this case, the inflection point is at about four months which is the month that is most likely for the vehicle to return for its normal inspection. The month-by-month difference between the two curves gives the change in failed miles driven that would be expected for this vehicle by calling it in and giving it a new certification:

$$\Delta FMD_{\text{Calling-In Sticker}} = FMD_{CS} - FMD_{NIM}$$

For the sample vehicle $\Delta FMD_{\text{Calling-In Sticker}}$ = -599 miles over the 24 months after the decision.

For some vehicles in some situations, the CS curve can cross over and be above the NIM curve for some period during the 24 months. Accordingly, when the differences are taken between the two curves, the direction of the subtraction for each month must be followed carefully. $\Delta FMD_{\text{Calling-In Sticker}}$ will be the smallest (that is, the largest negative) number for those vehicles that are most attractive to call-in under the Calling-In Sticker program. A sort of $\Delta FMD_{\text{Calling-In Sticker}}$ from the lowest values to the highest values will have the top candidates for Calling-In Sticker at the top of the list.

Figure 4-8. Comparison of Forecasted Failed Miles Driven for Calling-In Sticker and Normal I/M Process



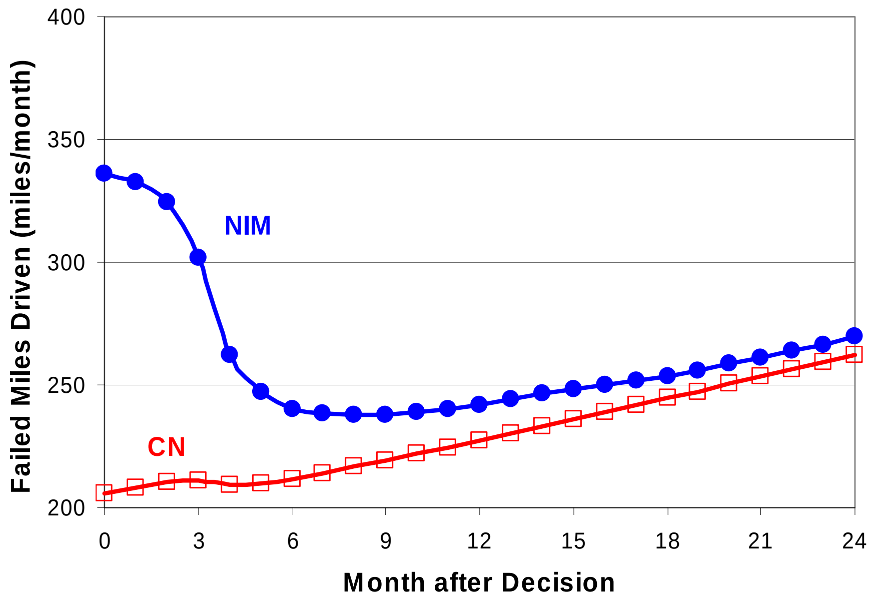
Calling-In No-Sticker – An alternative call-in program is one in which the vehicle is called in for inspection and potential repair. However, no new 24-month certification is given. After the call-in ASM the vehicle must still follow the current certification in the VID records. This situation is shown in Figure 4-9. Here both the NIM and the CN curves have inflections at four months since the vehicle was last inspected in the regular I/M program 21 months before the call-in ASM test in Month 0. The CN curve is below the NIM curve throughout the period because the vehicle received an ASM inspection and potential repair in Month 0. The change in failed miles driven for Calling-In No-Sticker is given by:

$$\Delta FMD_{\text{Calling-In No-Sticker}} = FMD_{CN} - FMD_{NIM}$$

For the sample vehicle $\Delta FMD_{\text{Calling-In No-Sticker}}$ = -803 miles over the 24 months after the decision.

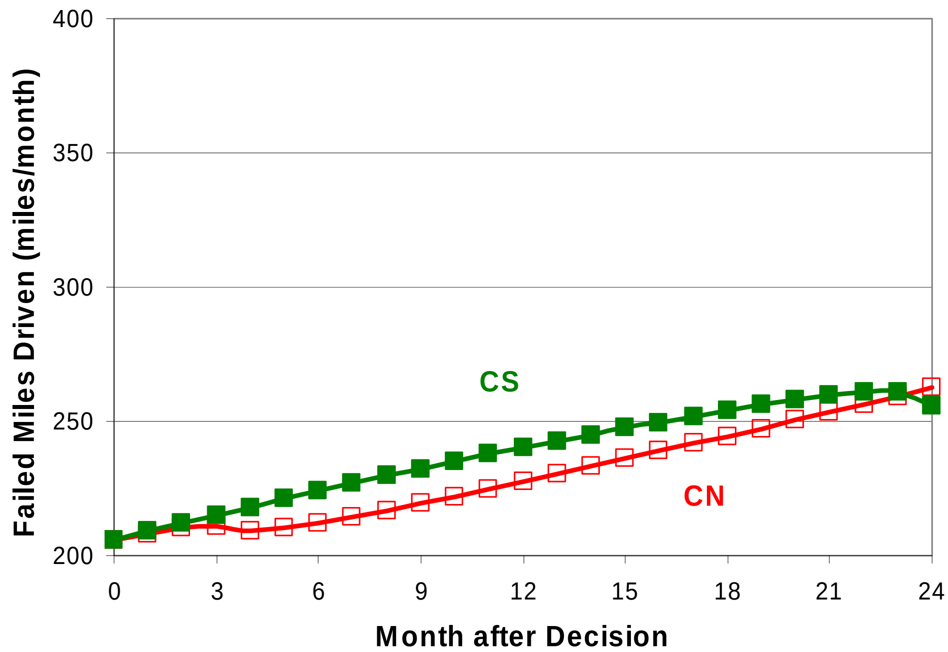
Just as for Calling-In Sticker, the most attractive vehicles for Calling-In No-Sticker will be those where $\Delta FMD_{\text{Calling-In No-Sticker}}$ is the smallest (that is, the largest negative) number. Thus, sorting the vehicles from low to high $\Delta FMD_{\text{Calling-In No-Sticker}}$ will produce a list that has the top candidates for Calling-In No-Sticker at the top of the list.

Figure 4-9. Comparison of Forecasted Failed Miles Driven for Calling-In No-Sticker and Normal I/M Process



At this point, it is worth examining the two alternative options for the call-in program: Sticker versus No-Sticker. Figure 4-10 shows the two curves for this vehicle for CS and CN. It is clear that the curve for CN is almost always below the curve for CS throughout the 24 months after the decision point. This means that a call-in program where no sticker is given at the call-in ASM will produce a greater benefit than if a sticker is given. However, in many cases, the difference between Sticker and No-Sticker in terms of failed miles driven over the 24 months may not be worth the public relations cost of asking people to come in for a call-in ASM test and then not giving them a new certification for their off-cycle effort. More comparisons of Calling-In Sticker and Calling-In No-Sticker should be examined before deciding on which is the more desirable policy.

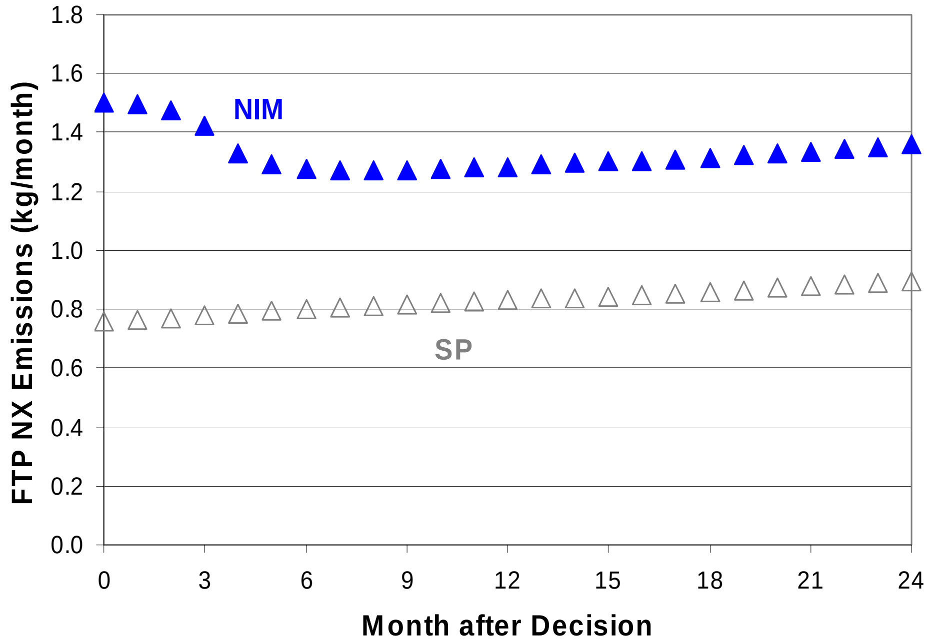
Figure 4-10. Comparison of Forecasted Failed Miles Driven for Calling-In Sticker and Calling-In No-Sticker



Scrapping – In the case of ranking vehicles for Scrapping candidates, the ranking variable is created from forecasted FTP mass emissions rather than from forecasted failed miles driven. The reason for this is that Scrapping eliminates all of the emissions – not simply the excess emissions. Figure 4-11 shows the forecasted FTP NX emissions that were calculated for the example vehicle in Section 4.2. The NIM curve gives the forecasted FTP mass emissions in kilograms per month for the case where the vehicle would not be scrapped but would remain under the Normal I/M Process. The lower curve is the forecasted mass emissions curve taking into account the probability that the vehicle would fail a scrappage ASM test in Month 0. That is, if the vehicle fails the scrappage test, its FTP emissions would be zero, but if the vehicle passes the scrappage ASM test it would continue to participate in the Normal I/M Process without receiving a new certification. The net change in FTP NX emissions for this case is given by:

$$\Delta FTP_{Scrapping} = FTP_{SP} - FTP_{NIM}$$

Figure 4-11. Comparison of Forecasted FTP Mass Emissions for Scrapping and Normal I/M Process



These monthly differences are then summed up for all 24 months after the decision point to arrive at the total ΔFTP. This value is then divided by the estimated market value of the vehicle to arrive at ΔFTP/$. For the sample vehicle $\Delta FTP_{Scrapping}$ = -12.6 kg NX over the 24 months since the decision. The estimate market value of the 17-year-old Taurus is $2,200, as calculated as described in Section 3.3. Thus, the Scrapping ΔFTP/$ ranking value for NX is -5.7 g/$.

Vehicles that have large negative values of ΔFTP/$ will be top candidates for Scrapping because, for every dollar of vehicle value, their scrappage would reduce FTP emissions by the greatest amount. Therefore, a ranking of vehicles by increasing values of ΔFTP/$ would put the most attractive Scrapping candidates at the top of the list.

Models C and D provide forecasted FTP mass emission curves such as those shown in Figure 4-11 where inflection points occur near the time when vehicles have the highest expected probability of completing their next regular I/M inspection. Because Model E does not have any time dependence, the curves for Model E do not look like those in Figure 4-11 but instead are horizontal lines with a constant value for the NIM curve that is above a lower constant value for the SP curve. In spite of the fact that the Model E NIM and SP curves are horizontal lines, rankings for Scrapping using Model E can still be made and may be reasonably accurate.

4.4 Results of Ranking Vehicles in the Pilot Dataset

Using the techniques described in the previous subsections, a SAS program[30] was used to create 35 different ranking variables for the 69,629 vehicles in the pilot dataset. Table 4-8 shows how the 35 ranking variables were derived from the six types of models and six different ranking criteria. The first three ranking criteria in the table (for vehicle ranking Methods 1 through 23) are described in Section 4.1. The other vehicle ranking criteria (for vehicle ranking methods 24 through 35) were added later as possible alternatives to the originally envisioned vehicle ranking methods. They will be discussed shortly.

Vehicle ranking Methods 1 through 8 are each custom designed to select vehicles to maximize the change in failed miles driven (ΔFMD) for Directing, Exempting, Calling-In No-Sticker, and Calling-In Sticker. Vehicle ranking Methods 9 through 17 are custom designed to select vehicles for Scrapping to maximize the change in FTP mass emissions (ΔFTP) over the 24 months after the Scrapping decision through the purchase of the vehicle by the State. Vehicle ranking Methods 18 through 23 are used to rank vehicles simply by their overall ASM failure probability at the decision point, which does not consider at all the change in failed miles driven, the change in FTP mass emissions, or the value of the vehicle when deciding vehicle rankings for Directing, Exempting, Calling-In No-Sticker, Calling-In Sticker, or Scrapping.

Of course, vehicle ranking Methods 1 through 23 are not the only methods that could be used to rank vehicles for selection for special I/M program strategies. After we developed and evaluated those vehicle ranking methods, we conceived of the other ranking methods shown in Table 4-8 as Methods 24 through 35. These methods are discussed next.

In essence, vehicle ranking Methods 9 through 17 rank vehicles so that when the State purchases vehicles for Scrapping, the funds are used to buy reductions in FTP mass emissions over the 24 months following the purchase. However, scrappage vehicle funds could alternatively be used to purchase reductions in other quantities. For example, in vehicle ranking Methods 24 through 29, scrappage funds are used to purchase vehicles that have the highest overall ASM failure probability at the decision point. Methods 24 through 29 are thus contrasted with Methods 18 through 23, which do not consider the value of the vehicle at all. Accordingly, we would expect that Methods 24 through 29 would be more cost-effective for identifying

[30] \bigrig\DecisionModel\SystemAnalysis\Core\Rank.sas.

Table 4-8. Categorization of the 35 Ranking Methods

Description of Vehicle Ranking Criterion		Vehicle Ranking Method	Model On Which the Vehicle Ranking is Based (Inputs)	Strategy That Ranking Method Can Be Used For				
				DI	EX	CN	CS	SP
Change in Failed Miles Driven Over 24 Months after the Decision Point (ΔFMD)	1	DI ΔFMD by C	C (VID History)	X				
	2	EX ΔFMD by C	C (VID History)		X			
	3	CN ΔFMD by C	C (VID History)			X		
	4	CS ΔFMD by C	C (VID History)				X	
	5	DI ΔFMD by D	D (VID History + RSD)	X				
	6	EX ΔFMD by D	D (VID History + RSD)		X			
	7	CN ΔFMD by D	D (VID History + RSD)			X		
	8	CS ΔFMD by D	D (VID History + RSD)				X	
Change in FTP Mass Emissions Over 24 Months after the Decision Point per Vehicle Value Dollar (ΔFTP/$)	9	ΔFTP HC/$ by C	C (VID History)					X
	10	ΔFTP CO/$ by C	C (VID History)					X
	11	ΔFTP NX/$ by C	C (VID History)					X
	12	ΔFTP HC/$ by D	D (VID History + RSD)					X
	13	ΔFTP CO/$ by D	D (VID History + RSD)					X
	14	ΔFTP NX/$ by D	D (VID History + RSD)					X
	15	ΔFTP HC/$ by E	E (ASM Cutpoints + RSD)					X
	16	ΔFTP CO/$ by E	E (ASM Cutpoints + RSD)					X
	17	ΔFTP NX/$ by E	E (ASM Cutpoints + RSD)					X
Fprob at Decision Point (FprobDP)	18	FprobDP by A	A (Model Year)	X	X	X	X	X
	19	FprobDP by B	B (Vehicle Description)	X	X	X	X	X
	20	FprobDP by C	C (VID History)	X	X	X	X	X
	21	FprobDP by D	D (VID History + RSD)	X	X	X	X	X
	22	FprobDP by E	E (ASM Cutpoints + RSD)	X	X	X	X	X
	23	FprobDP by F	F (RSD)	X	X	X	X	X
Fprob at Decision Point per Vehicle Value Dollar (FprobDP/$)	24	FprobDP/$ by A	A (Model Year)					X
	25	FprobDP/$ by B	B (Vehicle Description)					X
	26	FprobDP/$ by C	C (VID History)					X
	27	FprobDP/$ by D	D (VID History + RSD)					X
	28	FprobDP/$ by E	E (ASM Cutpoints + RSD)					X
	29	FprobDP/$ by F	F (RSD)					X
One-Time Observed RSD Emissions Concentration	30	RSD [HC]	No Model (Measured [RSD])	X	X	X	X	X
	31	RSD [CO]	No Model (Measured [RSD])	X	X	X	X	X
	32	RSD [NX]	No Model (Measured [RSD])	X	X	X	X	X
One-Time Observed RSD Emissions Concentration per Vehicle Value Dollar	33	RSD [HC]/$	No Model (Measured [RSD])					X
	34	RSD [CO]/$	No Model (Measured [RSD])					X
	35	RSD [NX]/$	No Model (Measured [RSD])					X

DI = Directing CS = Calling-In Sticker EX = Exempting
SP = Scrapping CN = Calling-In No-Sticker

vehicles with high overall ASM failure probabilities at the decision point. However, they would be less cost-effective than vehicle ranking Methods 9 through 17 in which funds are used to buy vehicles whose scrappage would produce the largest change in FTP mass emissions over the 24 months after the scrappage decision.

Another vehicle ranking criterion is to simply use the measured RSD emission concentration of vehicles to rank the vehicles. This method is not actually a failure probability model. It is similar to the method used by RSD vendors to target vehicles using so-called RSD cutpoints. Vehicles with the highest measured RSD concentration would be targeted for Directing, Calling-In, and Scrapping, and those with the lowest RSD concentrations would be targeted for Exempting. Because there are three different measured RSD concentrations for HC, CO, and NX, there are three possible vehicle ranking methods as shown in Table 4-8 by Methods 30 through 32. Of course, these ranking methods do not consider at all the change in failed miles driven over 24 months after the decision point, the change in FTP mass emissions over the 24 months after the decision point, the vehicle value, or even the overall ASM failure probability at the decision point when ranking vehicles for the I/M program strategies. Vehicle ranking Methods 30 through 32 would therefore not be expected to produce benefits as high as benefits for vehicle ranking methods that target specific vehicle ranking criteria. Finally, vehicle ranking Methods 33 through 35 are designed to use vehicle scrappage funds to purchase vehicles that have been observed with elevated RSD emissions concentrations. In essence, the funds are being used to purchase high RSD emission concentrations that were observed one time on the road. These methods are similar to Methods 30 through 32, but they take estimated vehicle value into account when ranking the vehicles.

Table 4-8 and the discussion above demonstrates that when ranking vehicles for special I/M program strategies by different vehicle ranking criteria the thoughtful agency will consider the trade-offs among the different types of benefits achieved for a given strategy. For a given strategy, vehicles can be ranked by only a single vehicle ranking criterion. The agency must choose which one it should be while recognizing the trade-offs. Specifically, which is the most important quantity to maximize: the reduction in failed miles driven over the 24 months after the decision point, the reduction in FTP mass emissions over the 24 months after the decision point, simply the failure probability at the decision point, which is one point in time, or the one point in time RSD emissions concentration? The inspection and emissions forecasting system described in this report has the capability of evaluating the size of the trade-offs that can help answer this question. With the system, ARB and BAR can make an informed decision about the strategies and the vehicle ranking methods that they prefer based on knowledge of the trade-offs that exist.

Dispersion of Ranking Values – The vehicle ranking values used by different ranking methods to rank individual vehicles do not themselves reveal the size of the benefits to be realized by the different methods. However, by examining the dispersity of the ranking variables for each method, we can begin to get a feel for the ability of the ranking methods to identify vehicles that are quite exceptional or outstanding from the rest of the fleet in the qualities that make them good targets for selection for special strategies.

Figure 4-12 compares the ranking values of Fprob at Decision Point calculated by Models A, B, C, D, E, and F. Figure 4-13 shows the same comparison for the highest 7,000 ranking values (top 10%) so that a more clear comparison can be seen in this region.

Figure 4-12. Ranking Values of ASM Overall Failure Probability at the Decision Point (All Observations)

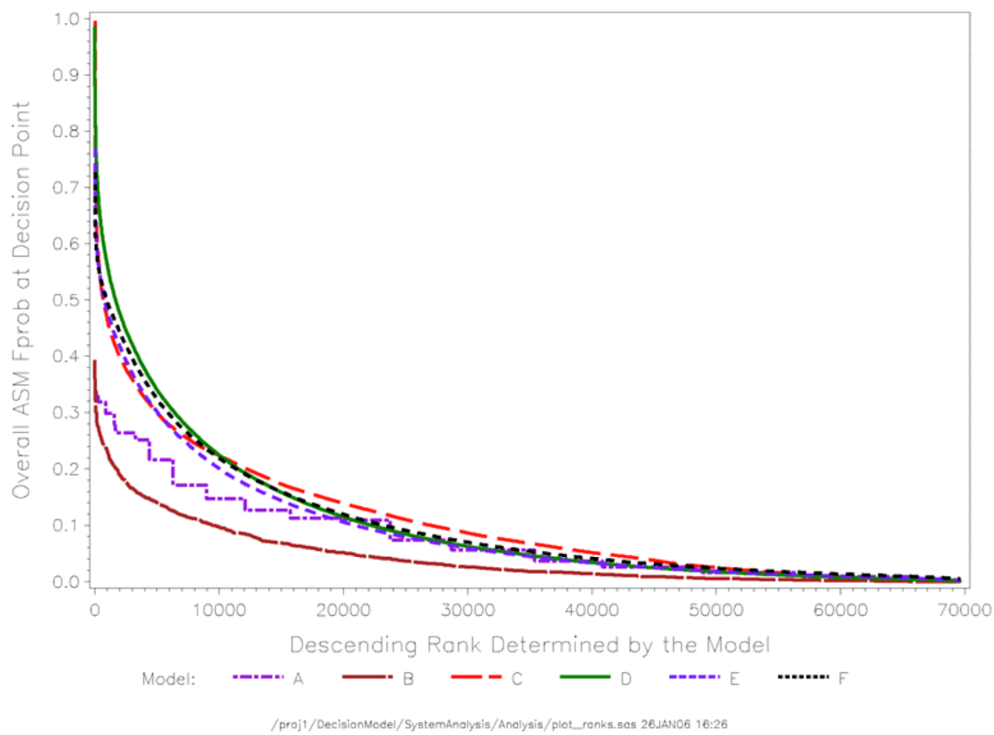
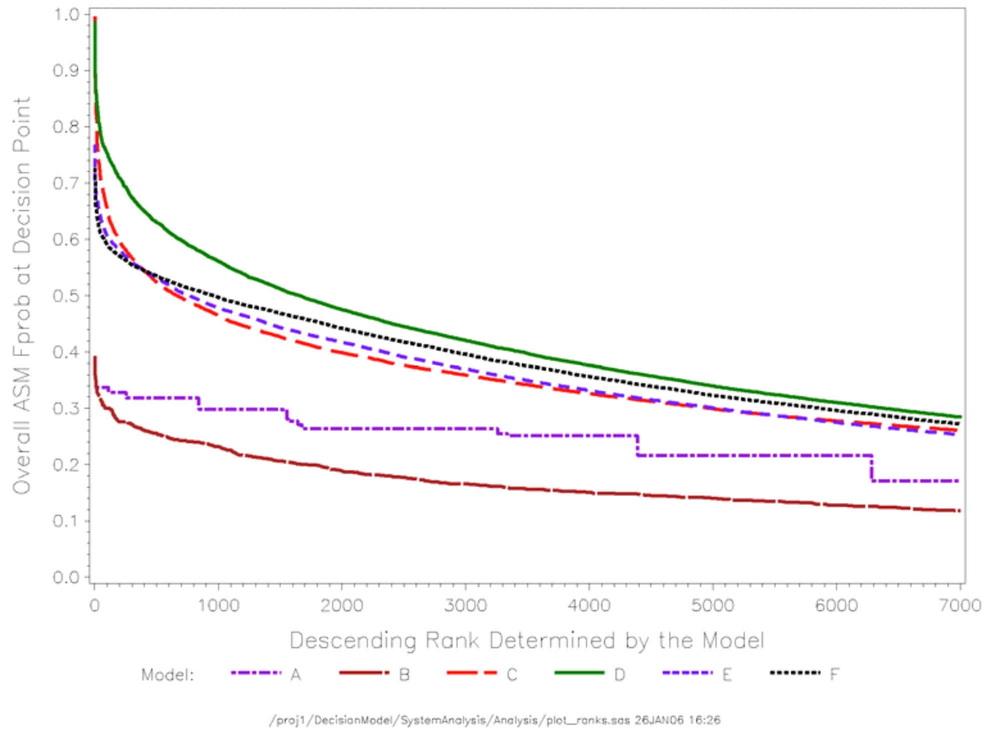


Figure 4-13. Ranking Values of ASM Overall Failure Probability at the Decision Point (Top 10% of Observations)



Figures 4-14, 4-15, 4-16, 4-17, and 4-18 show plots of the Overall ASM Fprobs at the Decision Point calculated by Models A, B, C, E, and F vs. the Overall ASM Fprob at the Decision Point by Model D for the 69,629 vehicles in the dataset. The plots are made with respect to the Model D results since Model D uses the most inputs of the six Fprob models. Because these inputs carry the most information, we believe the Model D Fprobs are the best estimates of the failure probability at the decision point. These plots show the differences in the spreads of the Fprobs from the different models. Models with more information tend to have a wider range of Fprobs. The plots also show that the correlation of Fprobs between the Fprobs of two models are highly scattered.

Figure 4-14. Comparison of Overall ASM Fprobs at Decision Point for Model A (Model Year) and Model D (VID History + RSD)

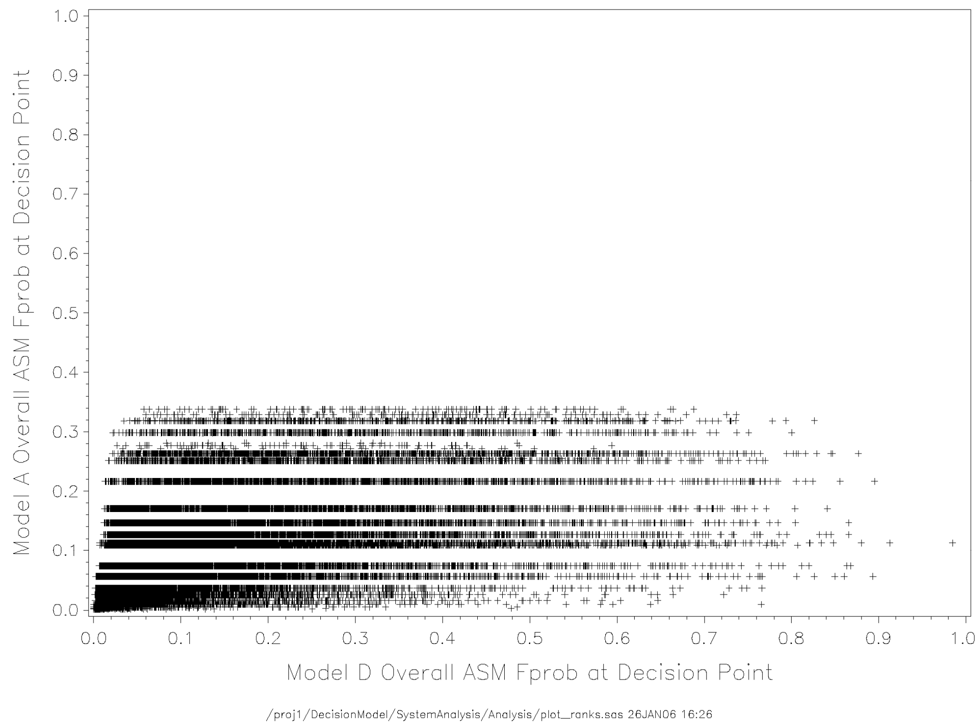


Figure 4-15. Comparison of Overall ASM Fprobs at Decision Point for Model B (Vehicle Description) and Model D (VID History + RSD)

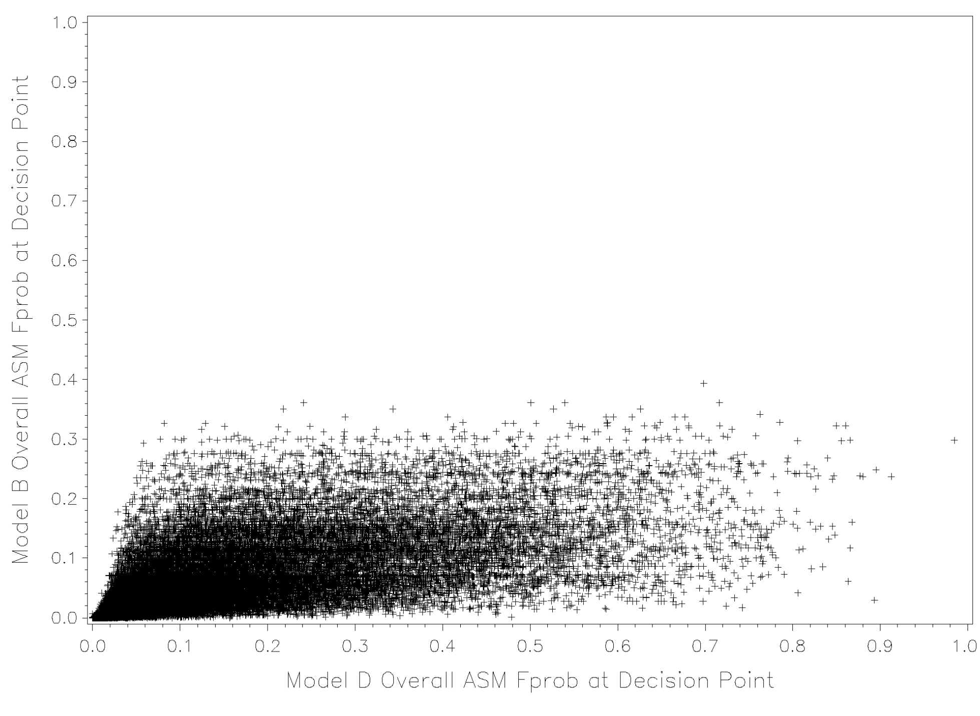


Figure 4-16. Comparison of Overall ASM Fprobs at Decision Point for Model C (VID History) and Model D (VID History + RSD)

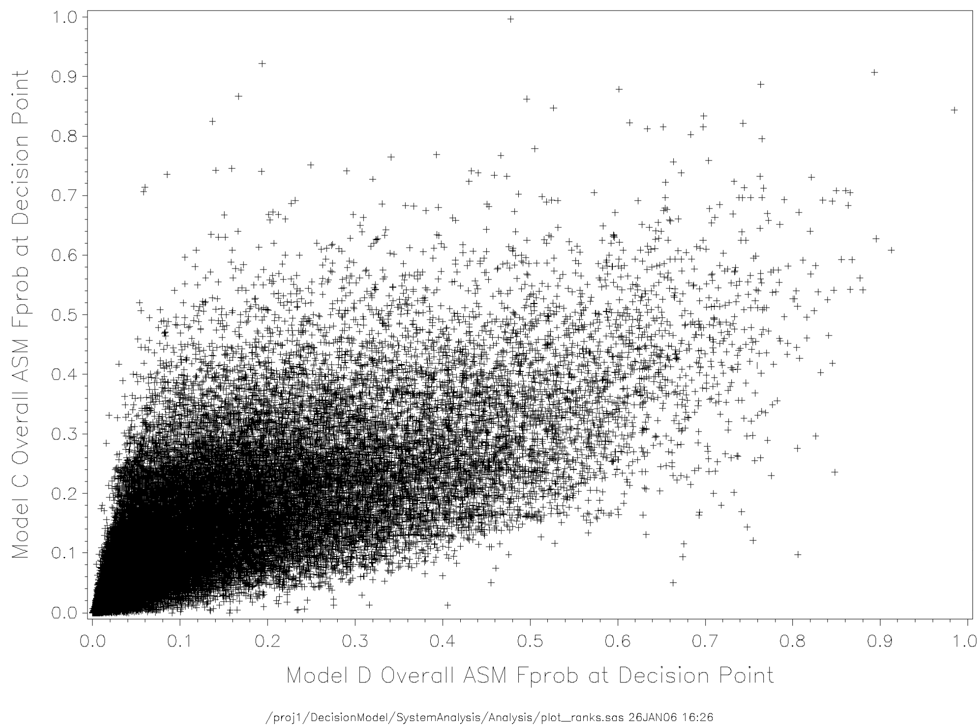


Figure 4-17. Comparison of Overall ASM Fprobs at Decision Point for Model E (ASM Cutpoints + RSD) and Model D (VID History + RSD)

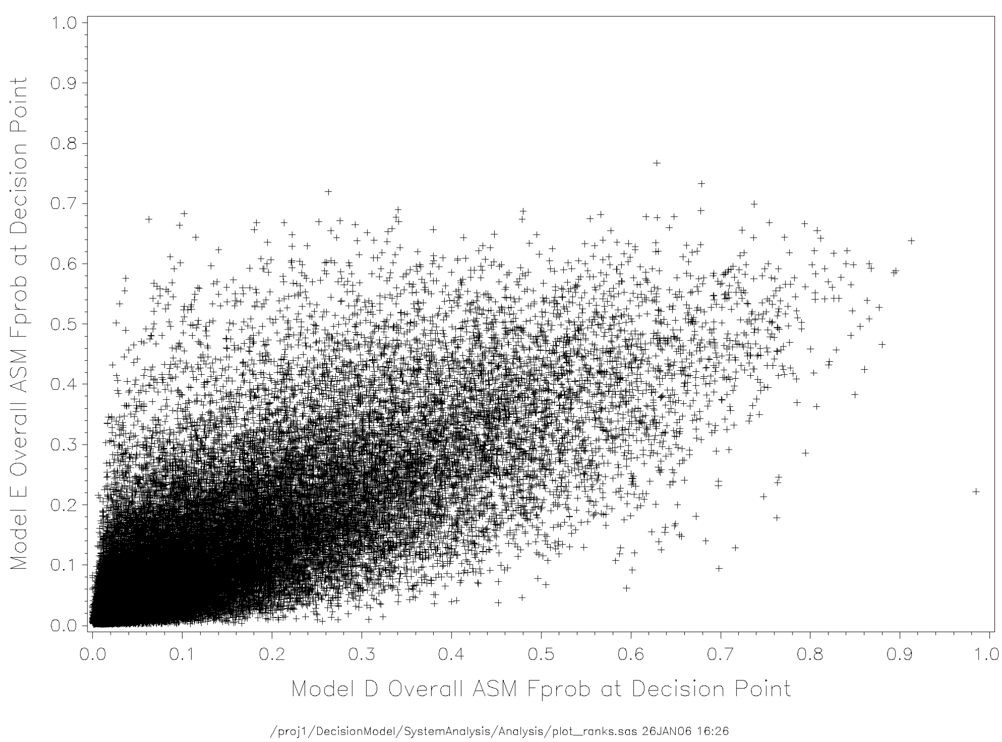
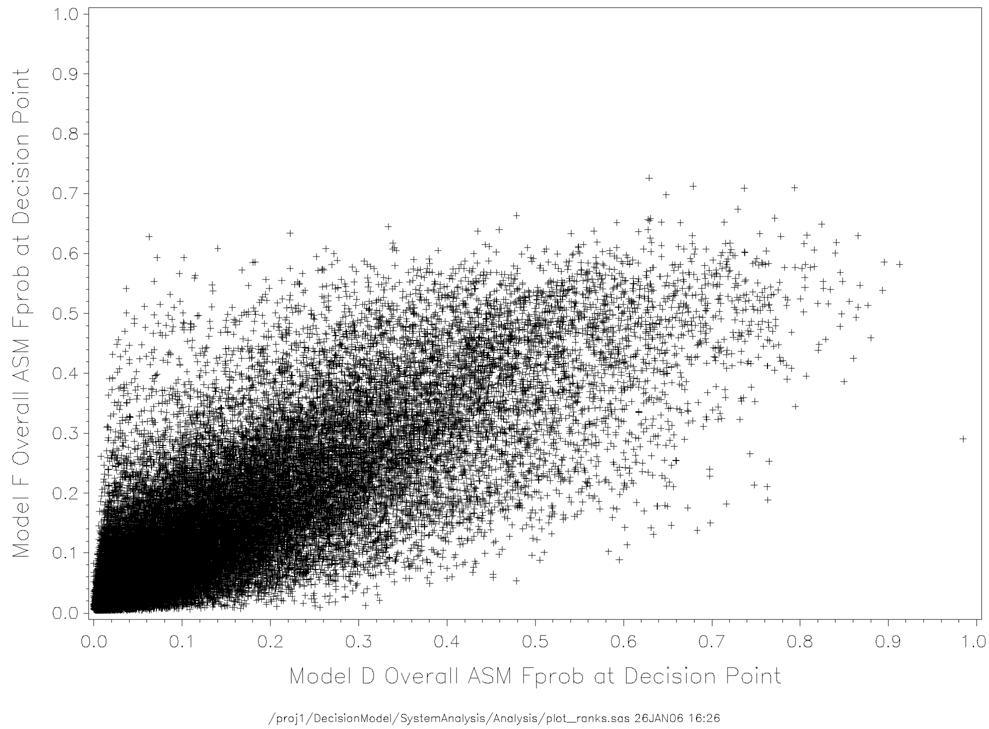


Figure 4-18. Comparison of Overall ASM Fprobs at Decision Point for Model F (RSD) and Model D (VID History + RSD)



Figures 4-19, 4-20, 4-23, and 4-25 compare the ΔFMD for the vehicle rankings of the dataset for Directing, Exempting, Calling-In No-Sticker, and Calling-In Sticker for Models C and D. These plots show the extent and diversity of the ranking values in the fleet. Figures 4-21, 4-22, 4-24, and 4-26 compare the individual vehicle ranking values from Model C against those from Model D for the same intervention strategies. These plots demonstrate the degree of similarity of ranking values provided by these two different time-dependent models.

For ranking vehicles for Scrapping, we need to calculate FTP HC, CO, and NX emissions for each vehicle for the Normal I/M Process path and for the Scrapping path. (When these values are combined with vehicle value, we get the ranking value of ΔFTP/$.) However, Models C, D, and E can each produce FTP emissions values. How well do these different model values agree with each other and with emission inventory values?

Figure 4-19. Ranking Values of Change in Failed Miles Driven for Directing

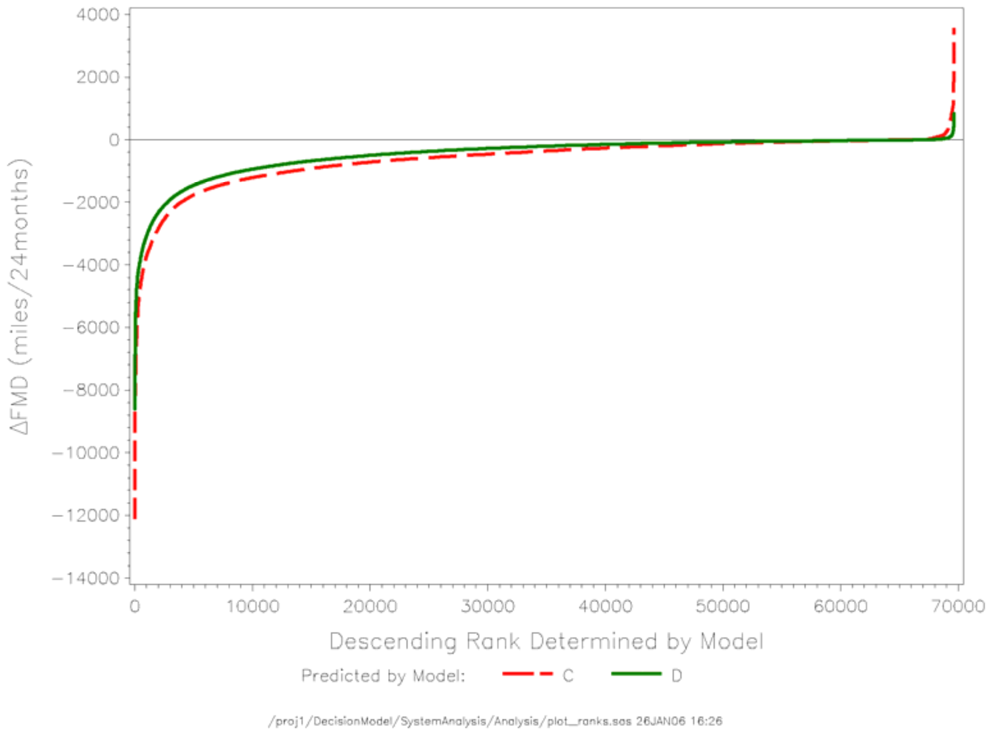


Figure 4-20. Ranking Values of Change in Failed Miles Driven for Exempting

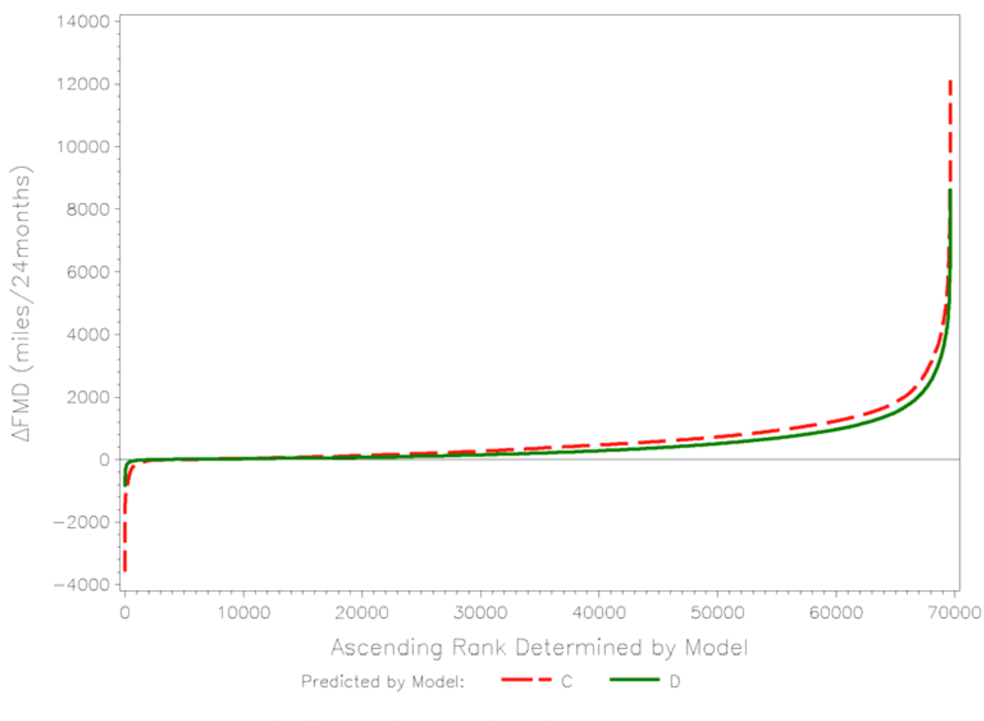


Figure 4-21. Comparison of Change in Failed Miles Driven Over 24 Months for Model C (VID History) and Model D (VID History + RSD) for Directing

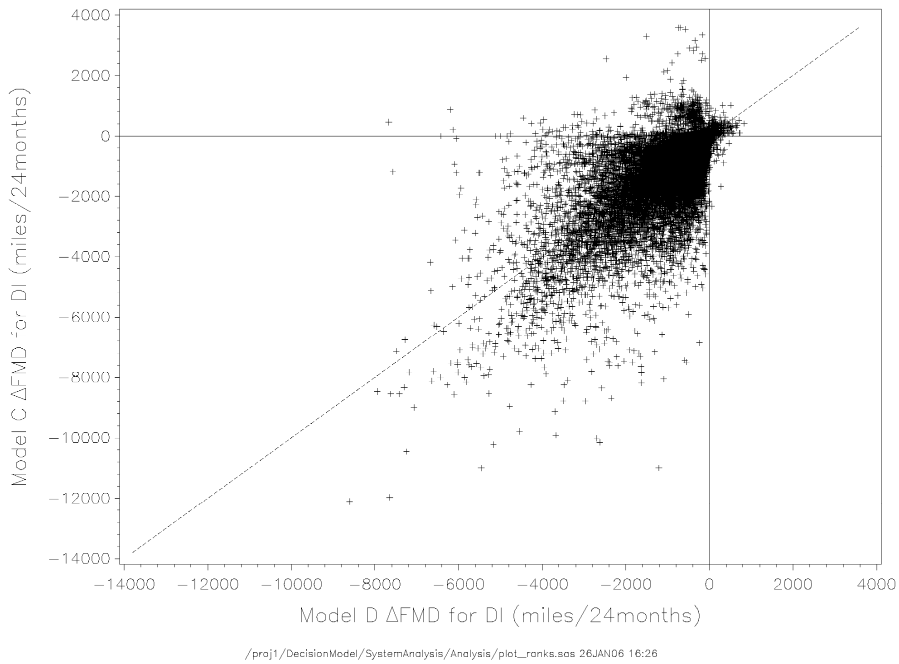


Figure 4-22. Comparison of Change in Failed Miles Driven Over 24 Months for Model C (VID History) and Model D (VID History + RSD) for Exempting

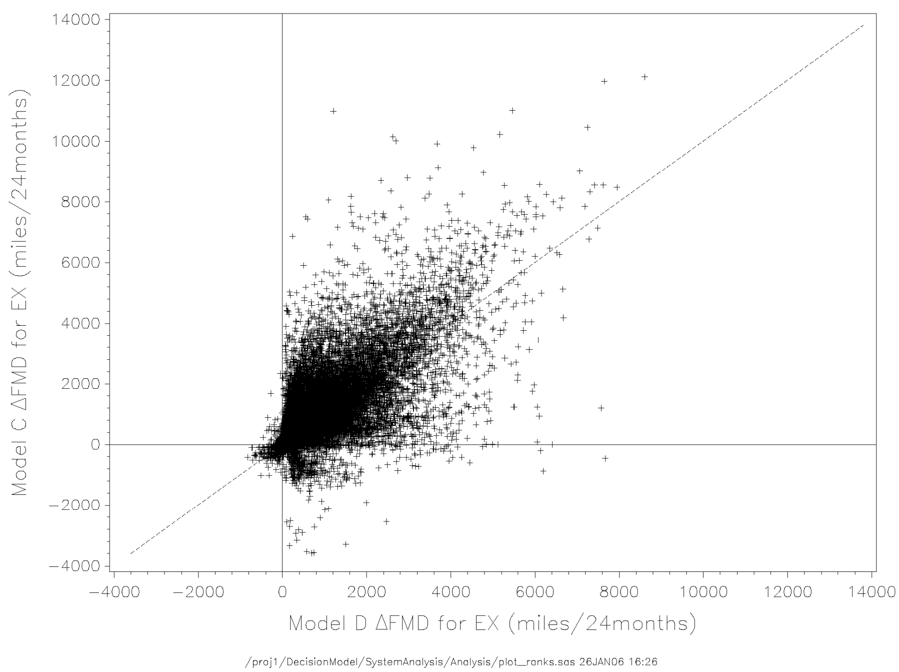


Figure 4-23. Ranking Values of Change in Failed Miles Driven for Calling-In No-Sticker

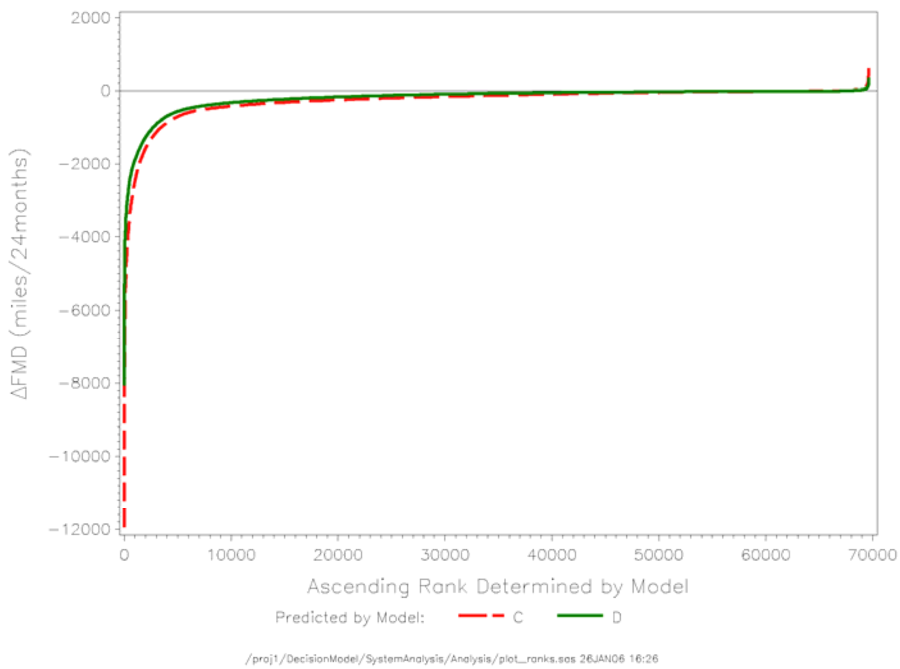


Figure 4-24. Comparison of Change in Failed Miles Driven Over 24 Months for Model C (VID History) and Model D (VID History + RSD) for Calling-In No-Sticker

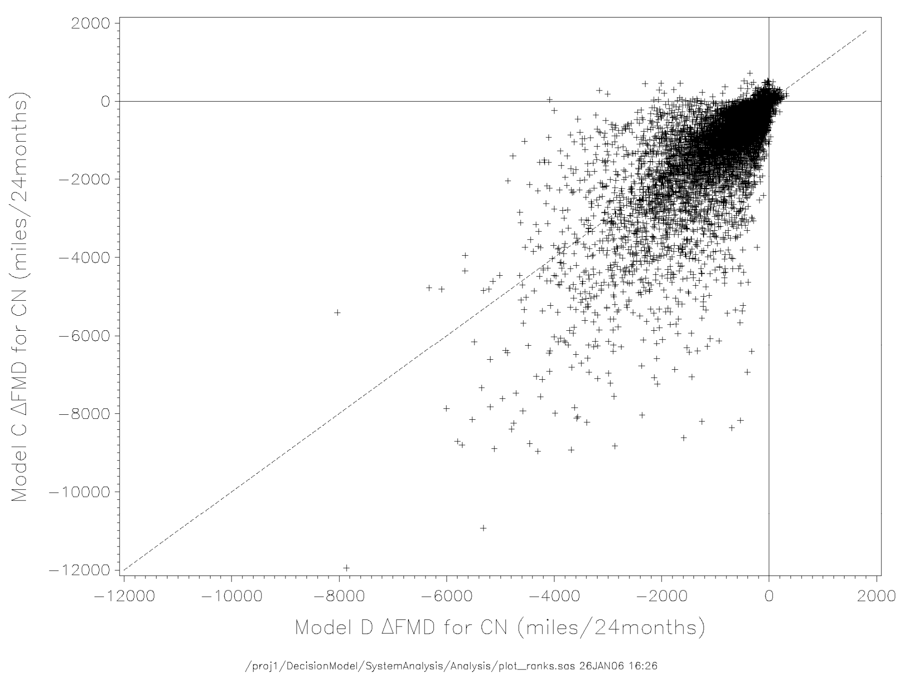


Figure 4-25. Ranking Values of Change in Failed Miles Driven for Calling-In Sticker

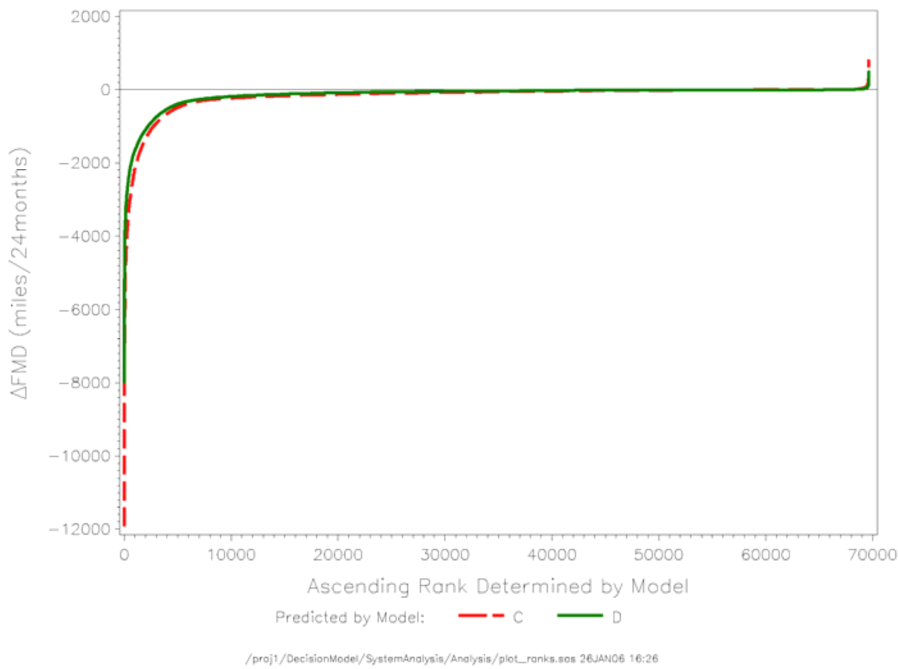
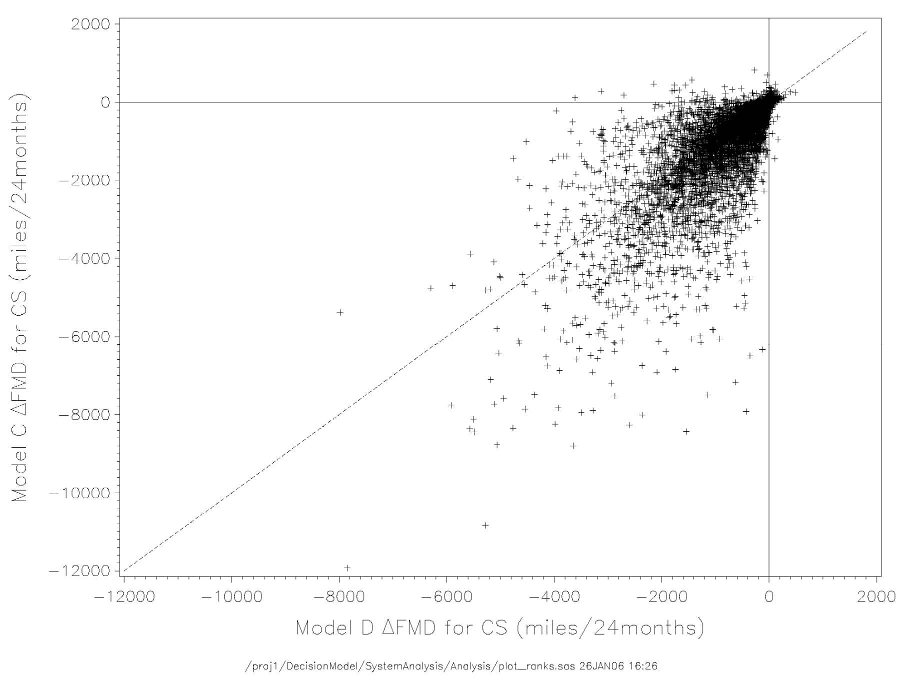


Figure 4-26. Comparison of Change in Failed Miles Driven Over 24 Months for Model C (VID History) and Model D (VID History + RSD) for Calling-In Sticker



If we sum the FTP mass emissions for the Normal I/M Process for each pollutant for the 69,629 vehicles in the dataset, divide the total by 730 days (since the emissions estimate is for 2 years), and ratio the answer up to the 13,388,069 1976-1998 I/M vehicles according to the 2004 ARB emissions inventory (see Appendix N), we arrive at the daily FTP emissions estimates using Models C, D, and E as shown in Table 4-9. These values are compared with EMFAC estimates of 1976-1998 model year light-duty car, light-duty truck, and medium-duty truck mobile source emissions inventory estimates for the 2004 calendar year, which are also given in Table 4-9. Model C and E values are below the emission inventory values and Model D values are above. The differences among the inventory estimates from Model C, D, and E arise from the differing models and the different types of data used to build them. The fact that Models C, D, and E produce different inventory estimates would be a concern if the goal of the study were to estimate the emission inventory; however, this study focuses primarily on estimating relative changes in the inventory. Therefore, the inventory estimate differences are not a major concern.

Table 4-9. I/M Fleet Exhaust Emissions Estimated from the 69,629 Vehicle Dataset Using Models C, D, and E

		Emissions Estimate (Metric tons/day)		
I/M Condition	**Estimate Source**	**HC**	**CO**	**NX**
Normal I/M Process	2004 Inventory Estimates[1]	256 (282 English)	4213 (4644 English)	423 (466 English)
	Model C (VID History)	**175** (-31%)	**2,263** (-46%)	**268** (-37%)
	Model D (VID History + RSD)	**547** (114%)	**5,731** (36%)	**496** (17%)
	Model E (RSD + ASM Cutpoint)	**176** (-31%)	**1,987** (-53%)	**231** (-45%)
No Further I/M	Model C (VID History)	**196** [12%]	**2,537** [12%]	**297** [11%]
	Model D (VID History + RSD)	**631** [15%]	**6,323** [10%]	**546** [10%]
	Model E[2]	**N/A**	**N/A**	**N/A**

[1]EMFAC run for 2004. See Appendix N for details.
( ): Percent deviation relative to official EMFAC estimate
[ ]: Percent deviation relative to the Normal I/M Process value for the same model.
[2]Model E is not able to make different FTP emissions estimates for the Normal I/M Process and No Further I/M because Model E is a non-time-dependent model.

Since we would like to compare the Scrapping ranking values (ΔFTP/$) from Models C, D, and E on an equal basis, we adjust the FTP values from the three models for the individual vehicles by the fleet totals in Table 4-9, so that all three model fleet totals would equal the

EMFAC emission inventory values. The mass of emissions adjusted to the total inventory basis is given by:

$$g_{Inv} = g_{Model\ X} * (\text{fleet total}_{Inv} / \text{fleet total}_{Model\ X})$$

where: Model X is Model C, D, or E.

For example, if the ΔFTP HC predicted by Model C is $-100 g_{Model\ C}$/24 month/$, then the adjusted value is $-146\ g_{Inv}$/24 month/$. Figures 4-27, 4-28, and 4-29 compare the ranking values (after adjusting) of ΔFTP/$ for FTP HC, CO, and NX for Scrapping using Models C, D, and E. Figures 4-30 to 4-38 compare the Scrapping ranking values (after adjusting) for the individual vehicles in the dataset among the three models. Note that these adjustments to a constant inventory basis are made only for the purposes of comparing model performance in Figures 4-27 to 4-38.

But we would also like to know if such modeled FTP value adjustments are reasonable. One check of this can be made by examining the fleet estimates by Models C and D for the No-Further-I/M situation, which are given in the lower half of Table 4-9. No-Further-I/M is the imaginary situation where all vehicles in the fleet would stop participating in the I/M program at the Decision Point. The emissions for the fleet would increase unchecked. The values in square brackets in Table 4-9 are percent changes in fleet emissions relative to the corresponding values for the Normal I/M Process case. The percent changes for corresponding pollutants produced by the two models are reasonably close to each other. Thus, even though the inventory estimates for exhaust HC, CO, and NX emissions from EMFAC, Model C, and Model D are quite different, the relative changes produced by "turning off" the I/M program for two years beginning at the Decision Point are quite similar for calculations by Model C and by Model D. This gives us some confidence that the relative changes calculated by Models C and D for other I/M program changes (such as Calling-In, Directing, Exempting, and Scrapping) are comparable with each other and represent reasonable estimates of the real emissions changes that would occur for such I/M program changes.

The comparison of fleet FTP estimates between the Normal I/M Process and No Further I/M represents a new method of measuring the annual I/M benefit in California. Model C provides estimates based on VID data; Model D provides estimates based on VID data plus RSD data.

Figure 4-27. Ranking Values of Change in FTP HC Mass Emissions per Vehicle Value Dollar (Top 1% of Rankings)

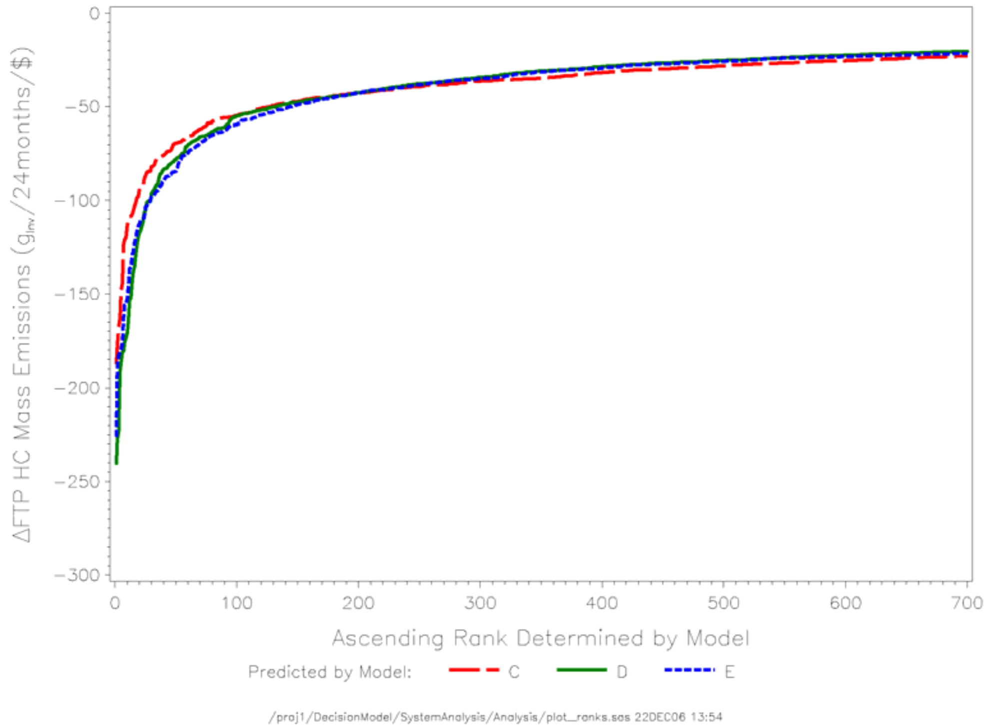


Figure 4-28. Ranking Values of Change in FTP CO Mass Emissions per Vehicle Value Dollar (Top 1% of Rankings)

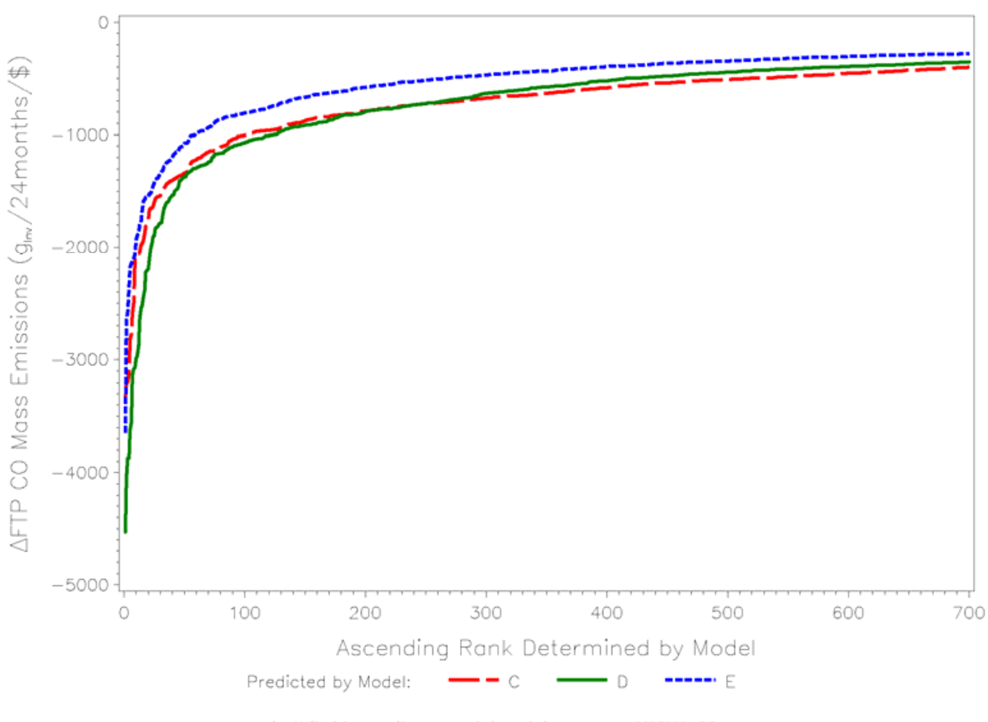


Figure 4-29. Ranking Values of Change in FTP NX Mass Emissions per Vehicle Value Dollar (Top 1% of Rankings)

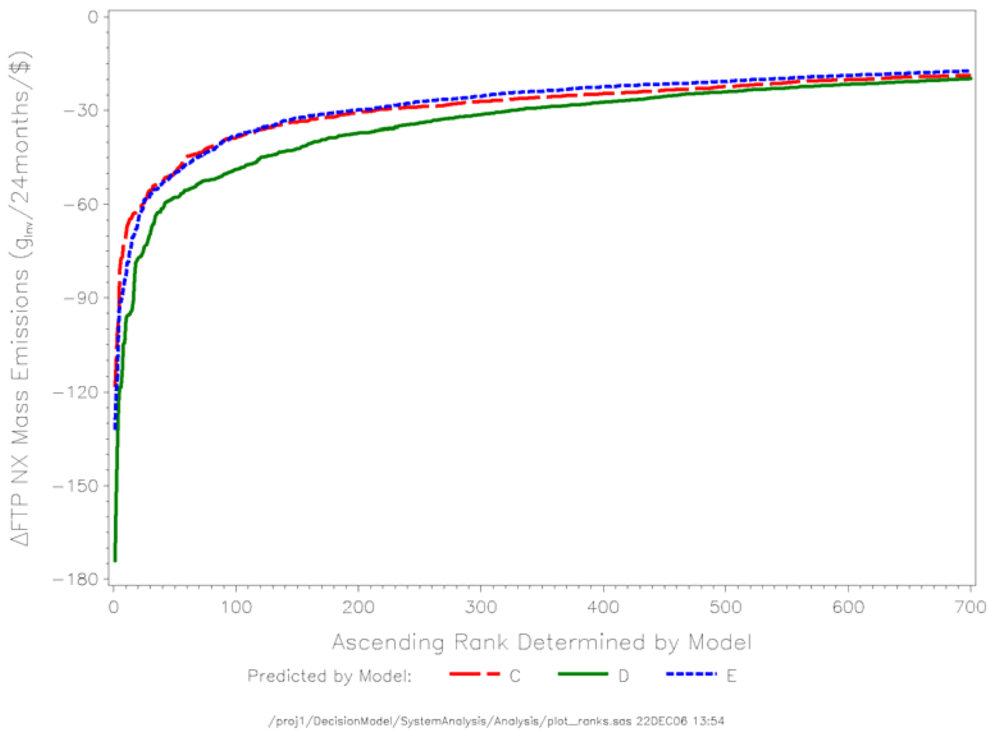


Figure 4-30. Comparison of Change in Failed Miles Driven Over 24 Months for Model C (VID History) and Model D (VID History + RSD) for Scrappage HC Ranking

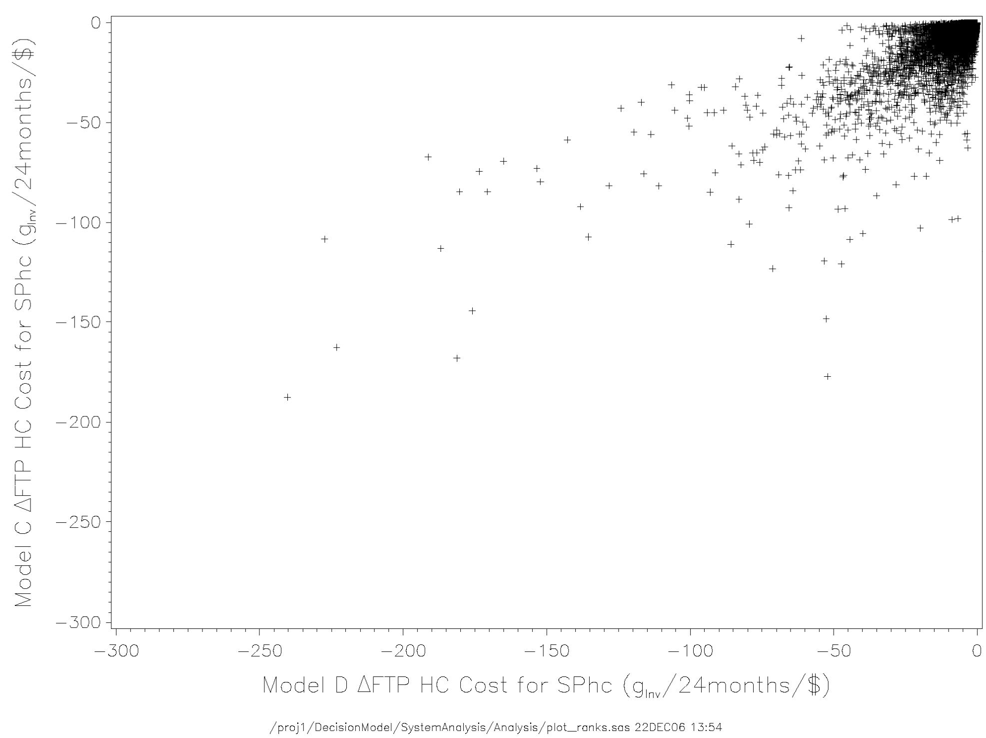


Figure 4-31. Comparison of Change in Failed Miles Driven Over 24 Months for Model E (RSD + ASM Cutpoints) and Model D (VID History + RSD) for Scrappage HC Ranking

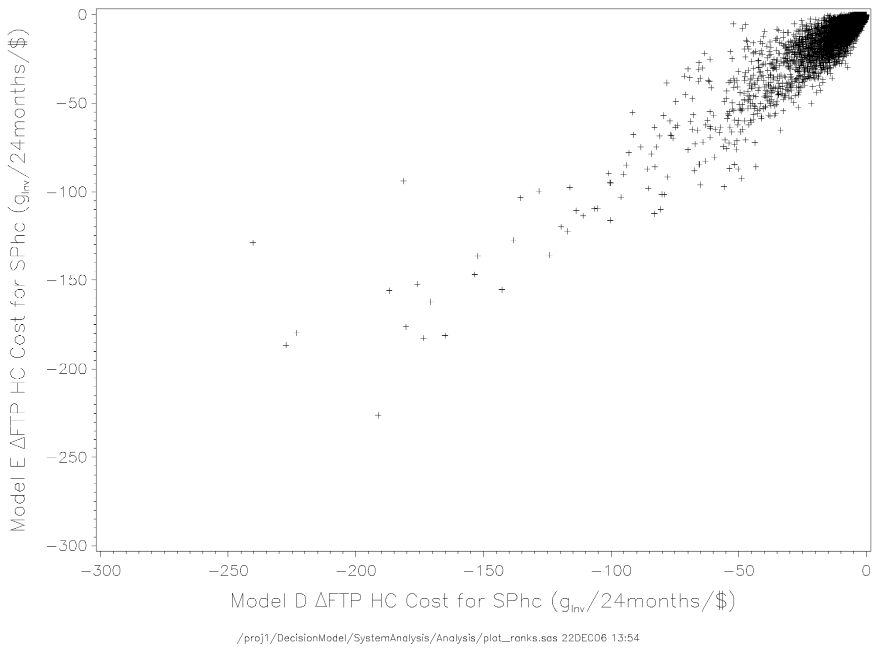


Figure 4-32. Comparison of Change in Failed Miles Driven Over 24 Months for Model E (RSD + ASM Cutpoints) and Model C (VID History) for Scrappage HC Ranking

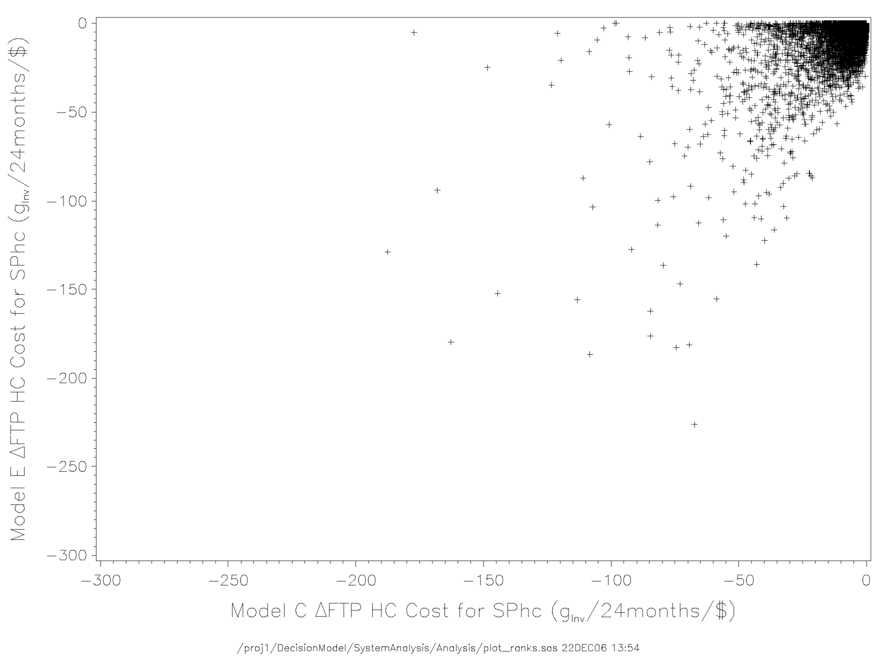


Figure 4-33. Comparison of Change in Failed Miles Driven Over 24 Months for Model C (VID History) and Model D (VID History + RSD) for Scrappage CO Ranking

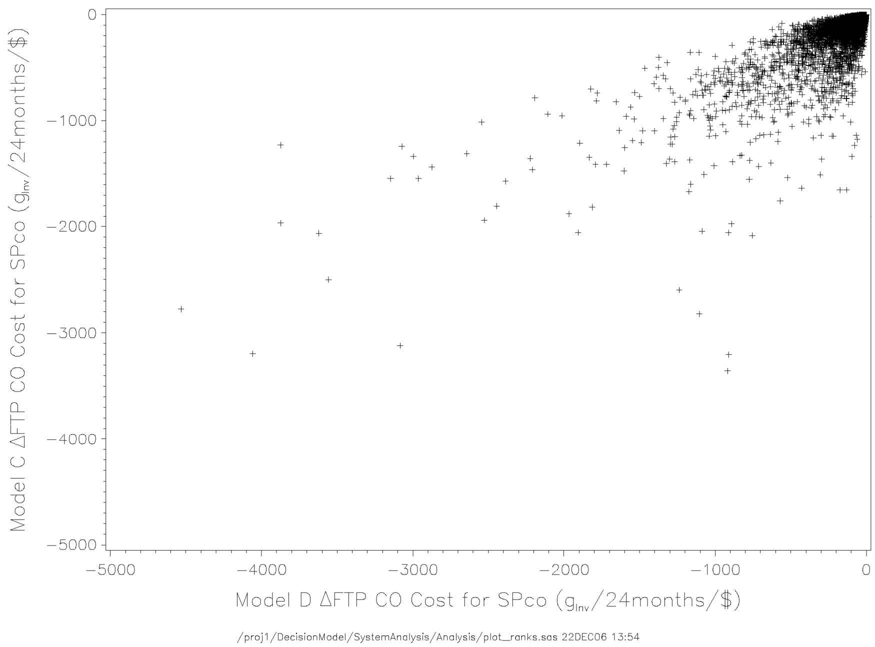


Figure 4-34. Comparison of Change in Failed Miles Driven Over 24 Months for Model E (RSD + ASM Cutpoints) and Model D (VID History + RSD) for Scrappage CO Ranking

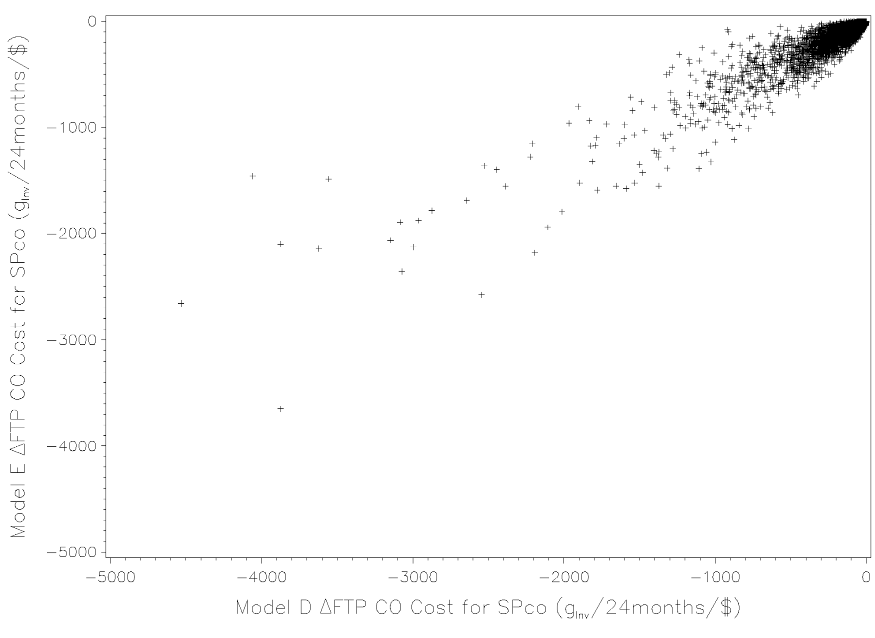


Figure 4-35. Comparison of Change in Failed Miles Driven Over 24 Months for Model E (RSD + ASM Cutpoints) and Model C (VID History) for Scrappage CO Ranking

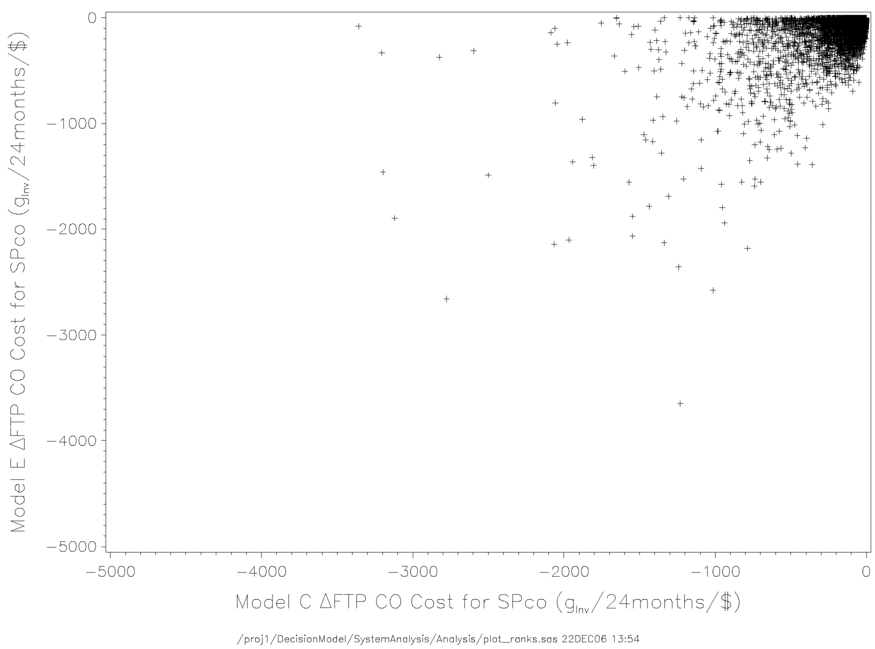


Figure 4-36. Comparison of Change in Failed Miles Driven Over 24 Months for Model C (VID History) and Model D (VID History + RSD) for Scrappage NX Ranking

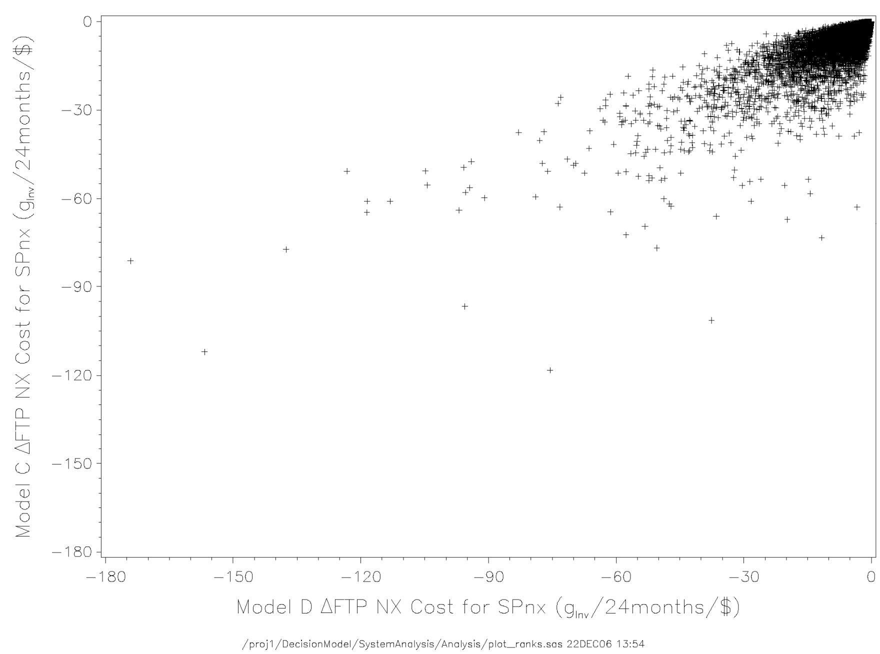


Figure 4-37. Comparison of Change in Failed Miles Driven Over 24 Months for Model E (RSD + ASM Cutpoints) and Model D (VID History + RSD) for Scrappage NX Ranking

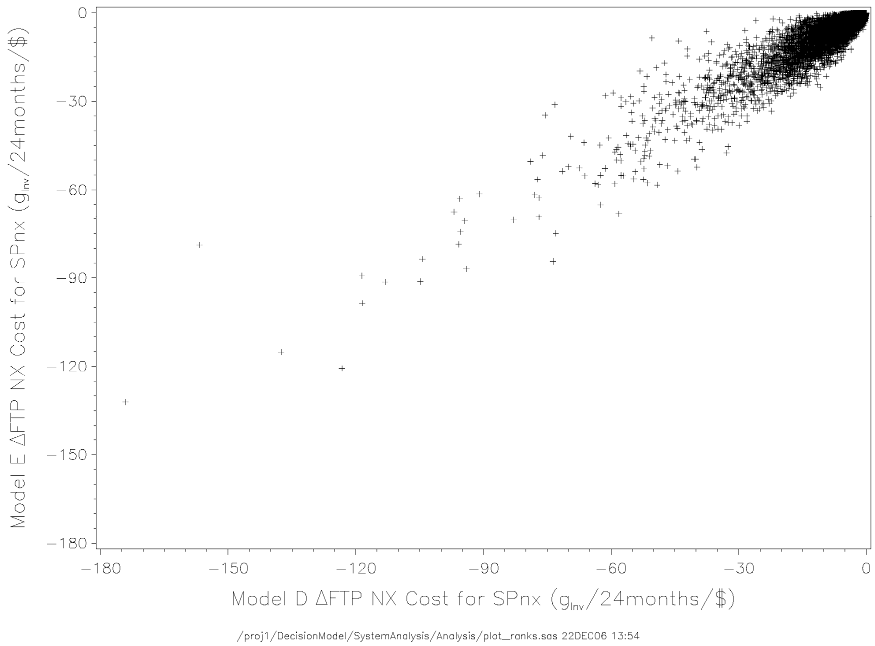
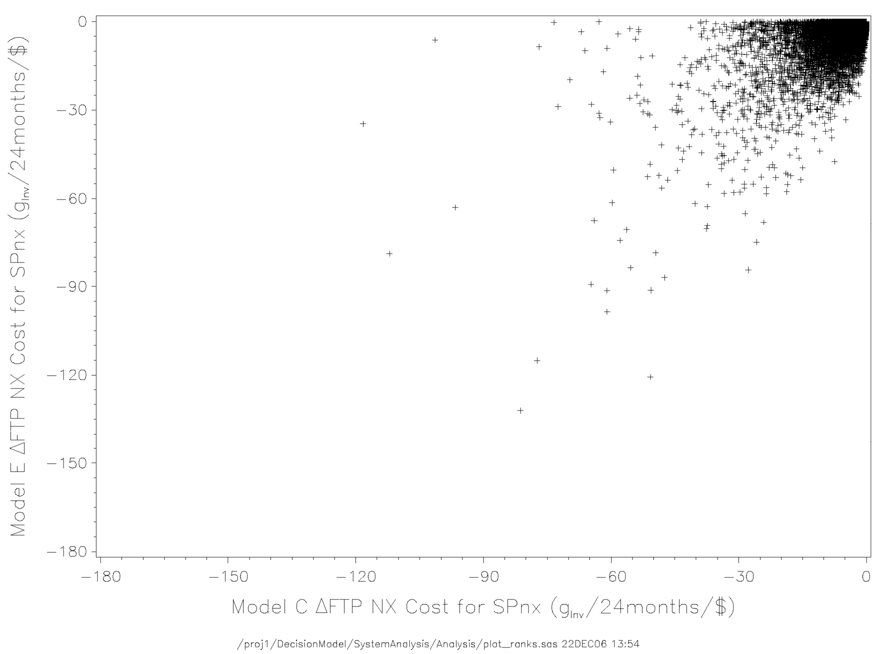


Figure 4-38. Comparison of Change in Failed Miles Driven Over 24 Months for Model E (RSD + ASM Cutpoints) and Model C (VID History) for Scrappage NX Ranking



4.5 Calculating Repair Cost Factors

When intervention strategies, such as Directing, Exempting, Calling-In, and Scrapping, are applied to the existing California I/M program, changes to the repair costs of individual vehicles that had been in the Normal I/M Process will occur. To evaluate the size of these incremental repair cost changes, we need to consider the size of the repair costs for the two paths under consideration for an individual vehicle: the Normal I/M Process path and the intervention strategy path. This subsection describes how the failure probability models and the I/M completion probabilities are used to forecast probable repair costs for individual vehicles for the different strategy decision choices: Directing, Exempting, Calling-In No-Sticker, Calling-In Sticker, Scrapping, and the Normal I/M Process.

The Total Repair cost for any path is made up of two parts:

Total Repair Cost = Decision Point Repair Cost + Future Repair Cost

The first part is the repair cost that may be incurred by repairs that are done at the Decision Point. Decision Point repairs occur only for the Calling-In strategies. Decision Point Repair Costs are not incurred for the Normal I/M Process, Directing, Exempting, and Scrapping since vehicles are not repaired at the Decision Point for those strategies. The second contribution to the Total Repair Cost for a given path is the cost incurred during the 48 months after the Decision Point for vehicle repairs that are induced by the existing I/M program. All of the paths (Normal I/M Process, Directing, Exempting, Calling-In, and Scrapping) have these Future Repair Costs.

In the discussion below, we describe the calculation of the Total Repair Costs for the Normal I/M Process and for Directing, Exempting, Calling-In, and Scrapping. We provide specific examples to demonstrate the repair costs. In this discussion, we use a unit repair cost of $194 for convenience. If the unit repair cost is different, another unit repair cost can be used.

Another future work effort is reserved for the development of more accurate estimates of repair costs. Specifically, we know that the results presented below have some biases as a consequence of estimating the future failure probabilities for only a single cycle. To properly compare repair costs between different strategies, the costs need to instead be calculated over the same calendar period, which involves calculating Fprobs up to two I/M cycles into the future. While this can be done, it is beyond the scope of this study. We have not performed detailed calculations using the same-calendar-period approach, but our estimates using that method indicate that the relative repair costs, as calculated below, are approximately equal to the more accurately calculated costs.

Repair Costs for the Normal I/M Process – For the Normal I/M Process there are no Decision Point Repair Costs since the vehicle is not called in at the Decision Point. All of the Total Repair Costs are Future Repair Costs since they are incurred in the 48 months following the Decision Point.

For the Normal I/M Process, a vehicle will come in for its next-cycle ASM inspection in some month following the Decision Point. Whichever month it comes in, the vehicle will receive an ASM test and there is a probability that it will fail the I/M test and then receive a repair. The probable cost of the repair is $194 times the failure probability in the month of the ASM inspection. The failure probability in that month is calculated based on the previous-cycle ASM result and the time since the previous cycle.

While we do not know in which month the vehicle will receive its next-cycle ASM inspection, we do know the probability that the vehicle will be inspected in any one of the 48 months after the Decision Point. The probability that a vehicle gets inspected during a given month is greatest during the period around 24 months since its previous-cycle ASM inspection. These monthly inspection probabilities are given by the brown ΔCprobs, which are discussed in Section 3.1.

The probable Total Repair Cost for a vehicle in the Normal I/M Process is therefore, the weighted sum of the probable repair costs in each of the months where the weighting factors are the brown ΔCprobs, which quantify the probability that the vehicle will return for its next-cycle ASM test in any given month.

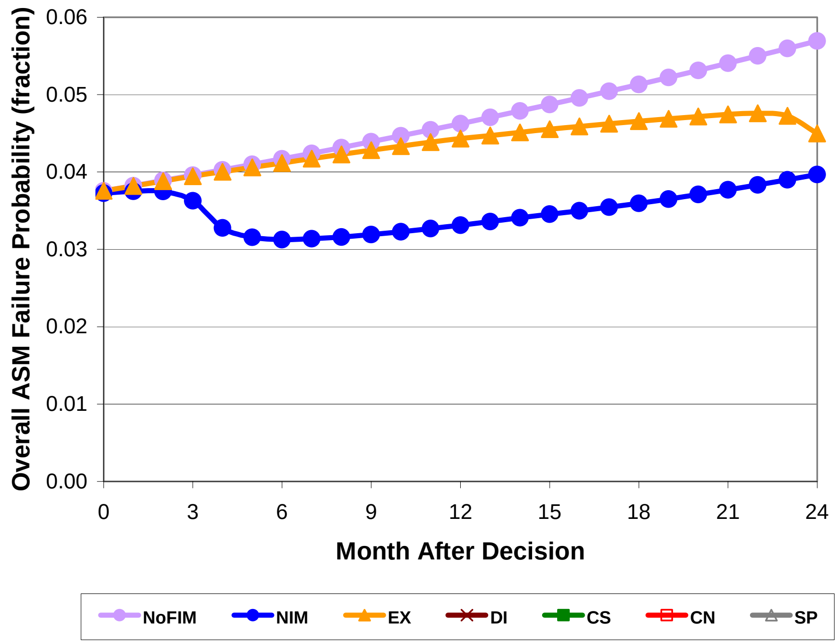
Table 4-10 shows the simulation conditions and Figure 4-39 shows overall ASM failure probability curves for a specific vehicle description that we will use to demonstrate the calculation of repair costs. To demonstrate the costs for the Normal I/M Process, Exempting, and Directing, we have chosen a situation for a low-emitting vehicle that had its previous I/M cycle 21 months before the Decision Point, which is the current month. We know this vehicle is a low-emitting vehicle because it passed all of its previous-cycle ASM tests and its RSD measurements were all very low. The vehicle's failure probability at Month 0 is 0.0369 as shown in Figure 4-39.

Table 4-10. Simulation Conditions for the Low-Emitting Example Vehicle

Vehicle:	1988 Ford Car 3.0L V6 FNTE
Monthly VMT:	1,000 miles
Previous-Cycle ASM Results:	
HC2525	Pass
CO2525	Pass
NX2525	Pass
HC5015	Pass
CO5015	Pass
NX5015	Pass
Time Information:	
Current Date:	03/13/03
Months Since Previous Cycle:	21
Recent RSD Measurements:	
HC	-466.7 ppm
CO	-0.3%
NX	-1,826.8 ppm
Future ASM Cutpoints:	
HC2525:	93 ppm
HC5015:	118 ppm
CO2525:	0.64%
CO5015:	0.76%
NX2525:	738 ppm
NX5015:	799 ppm

Figure 4-39 shows three overall ASM failure probability curves for three different situations. The upper purple curve shows the No Further I/M (NoFIM) trend in failure probabilities that are expected for the future. This represents the case if the vehicle, which has been participating in I/M program, no longer participates after Month 0. The bottom blue curve shows the expected failure probability for the vehicle as it continues to participate in the Normal I/M Process. The failure probability takes a dip around Month 3 since the previous I/M cycle was 21 months ago and the California I/M program is a biennial program. The orange curve between the other two curves with the triangle symbols represents the expected failure probability of the vehicle if it were exempted from the scheduled I/M inspection in Month 3. The curve shows that the failure probability continues to go up after Month 0. However, it does not go as high as the NoFIM curve since there is a probability that the vehicle will come in for an early or a change of ownership inspection some time during the next 24 months. The curves in the plot show that Exempting achieves a delay in the next I/M inspection at the expense of higher failure probability. This is seen by a comparison of the Exempting curve with the Normal I/M Process curve.

Figure 4-39. Forecasted Failure Probabilities for the Low-Emitting Vehicle for Exempting



/bigrig/DecisionModel/IMsimulator/IMsimulator_v03c_CprobCont_repcosts.xls

As we described above, the repair costs for any particular path are made up of the repair costs at the Decision Point and the Future Repair Costs. For the Normal I/M Process and the conditions shown in Table 4-11, the values for repair costs are calculated as shown in Table 4-11. The first column in Table 4-11 gives the month after the Decision Point. The Decision Point is the day before Month 0. The second column gives the failure probability of the vehicle if it would receive an ASM test at an I/M station.[31] Table 4-11 shows that these failure probabilities go up relatively linearly over the 48-month period. This increase is a consequence of vehicle aging. The third column gives the probable repair cost if the vehicle would get inspected in any particular month. This is simply the value of the failure probability in the second column times the unit repair cost of $194.

[31] These failure probabilities are taken from the same calculations described earlier for the calculation of failed miles driven. For example, the failure probability for a vehicle coming in for an ASM test in Month 4 for the Normal I/M Process is given in Table 4-2 in Column I in the cell just above the thick black line, where Y=3. (The value in Table 4-11 is different from the value in Table 4-2 because the vehicle conditions are different.)

Table 4-11. Sample Calculation of Repair Costs for the Normal I/M Process

Month	Fprob	Probable Repair Cost If the Vehicle Gets Inspected In the Indicated Month ($)	Likelihood that the Vehicle Will Get an Inspection In the Indicated Month (Brown ΔCprob)	Likely Future Repair Cost Incurred In a Given Month ($)	Probable Decision Point Repair Cost for NIM ($)
Decision Point	0.0369				$0.00
0	0.0369	7.16	0.0339	0.24	
1	0.0376	7.29	0.0382	0.28	
2	0.0382	7.42	0.0644	0.48	
3	0.0389	7.55	0.1662	1.25	
4	0.0396	7.68	0.3502	2.69	
5	0.0403	7.81	0.1425	1.11	
6	0.0410	7.95	0.0650	0.52	
7	0.0417	8.09	0.0330	0.27	
8	0.0424	8.23	0.0210	0.17	
9	0.0432	8.37	0.0154	0.13	
10	0.0439	8.52	0.0119	0.10	
11	0.0447	8.67	0.0097	0.08	
12	0.0455	8.82	0.0068	0.06	
13	0.0463	8.97	0.0054	0.05	
14	0.0471	9.13	0.0047	0.04	
15	0.0479	9.29	0.0064	0.06	
16	0.0487	9.45	0.0080	0.08	
17	0.0496	9.62	0.0067	0.06	
18	0.0504	9.79	0.0044	0.04	
19	0.0513	9.96	0.0037	0.04	
20	0.0522	10.13	0.0010	0.01	
21	0.0531	10.31	0.0014	0.01	
22	0.0541	10.49	0.0000	0.00	
23	0.0550	10.67	0.0000	0.00	
24	0.0560	10.86	0.0000	0.00	
25	0.0569	11.05	0.0000	0.00	
26	0.0579	11.24	0.0000	0.00	
27	0.0590	11.44	0.0000	0.00	
28	0.0600	11.64	0.0000	0.00	
29	0.0610	11.84	0.0000	0.00	
30	0.0621	12.05	0.0000	0.00	
31	0.0632	12.26	0.0000	0.00	
32	0.0643	12.48	0.0000	0.00	
33	0.0654	12.69	0.0000	0.00	
34	0.0666	12.92	0.0000	0.00	
35	0.0678	13.15	0.0000	0.00	
36	0.0690	13.38	0.0000	0.00	
37	0.0702	13.61	0.0000	0.00	
38	0.0714	13.85	0.0000	0.00	
39	0.0727	14.10	0.0000	0.00	
40	0.0740	14.35	0.0000	0.00	
41	0.0753	14.60	0.0000	0.00	
42	0.0766	14.86	0.0000	0.00	
43	0.0780	15.12	0.0000	0.00	
44	0.0793	15.39	0.0000	0.00	
45	0.0808	15.67	0.0000	0.00	
46	0.0822	15.95	0.0000	0.00	
47	0.0837	16.23	0.0000	0.00	
48	0.0852	16.52	0.0000	0.00	

Probable Future Repair Cost for NIM	Probable Decision Point Repair Cost for NIM	Probable Total Repair Cost for NIM
$7.78	$0.00	$7.78

Of course, we do not know which month in the future the vehicle will get inspected. Therefore, we do not know which probable repair cost from Column 3 would be incurred. However, we do know the probability that the vehicle will get inspected in each of the given 48 months. This is given by the brown ΔCprobs listed in the fourth column. These values are based on the fact that the vehicle was previously inspected 21 months before the Decision Point. The month of highest probability for the next inspection is Month 4. If we multiply the probability that the vehicle will get inspected in any particular month, which is given in Column 4, by the probable repair costs if the vehicle gets inspected in that month, which is given in Column 3, we get the contribution from each month toward the probable future repair cost which is given in Column 5. The sum of all these monthly costs gives us the total probable Future Repair Cost for NIM, which for this example is $7.78. As also shown in the table, the probable Decision Point Repair Costs for NIM is 0 and, therefore, the probable Total Repair Cost for this NIM example is $7.78. This is a reasonable value given that the overall ASM failure probability curve in Figure 4-39 shows that the failure probability for this vehicle over the period in question is about 0.04 and the unit repair cost is $194.

Repair Costs for Exempting – Repair costs for Exempting can be thought of in the same way as repair costs for the Normal I/M Process. First of all, there is no Decision Point Repair Cost incurred since vehicles are not called in for an ASM test when they are exempted. All of the repair costs incurred by a vehicle that is exempted occur in the month during the 48 months after the Decision Point when the vehicle comes in for its next-cycle ASM inspection.

Just as for the Normal I/M Process, we can calculate the probable repair cost of an exempted vehicle if it comes in for its next-cycle ASM inspection in a given month. As shown in Columns 2 and 3 of Table 4-12, this is simply the unit repair cost of $194 times the probability that the vehicle will fail an ASM test in the month in which it comes in. The failure probability for the month in which it comes in is based on the previous-cycle ASM result and the time since that cycle, which is 21 months, just as it was for the Normal I/M Process.[32] Note that the failure probabilities and the resulting probable repair costs for all months in Table 4-12 for Exempting are exactly the same as those in Table 4-11 for the Normal I/M Process.

[32] These failure probabilities are taken from the same calculations described earlier for the calculation of failed miles driven. For example, the failure probability for a vehicle coming in for an I/M program ASM test in Month 4 for Exempting is given in Table 4-3 in Column I in the cell just above the thick black line, where Y=3. (The value in Table 4-12 is different from the value in Table 4-3 because the vehicle conditions are different.)

Table 4-12. Sample Calculation of Repair Costs for Exempting

Month	Fprob	Probable Repair Cost If the Vehicle Gets Inspected In the Indicated Month ($)	Likelihood that the Vehicle Will Get an Inspection In the Indicated Month (Pink ΔCprob)	Likely Future Repair Cost Incurred In a Given Month ($)	Probable Decision Point Repair Cost for EX ($)
Decision Point	0.0369				$0.00
0	0.0369	7.16	0.000972	0.01	
1	0.0376	7.29	0.002263	0.02	
2	0.0382	7.42	0.003458	0.03	
3	0.0389	7.55	0.005556	0.04	
4	0.0396	7.68	0.009133	0.07	
5	0.0403	7.81	0.010711	0.08	
6	0.0410	7.95	0.011364	0.09	
7	0.0417	8.09	0.011875	0.10	
8	0.0424	8.23	0.012359	0.10	
9	0.0432	8.37	0.012764	0.11	
10	0.0439	8.52	0.013231	0.11	
11	0.0447	8.67	0.014490	0.13	
12	0.0455	8.82	0.018073	0.16	
13	0.0463	8.97	0.021958	0.20	
14	0.0471	9.13	0.020300	0.19	
15	0.0479	9.29	0.019782	0.18	
16	0.0487	9.45	0.021395	0.20	
17	0.0496	9.62	0.021559	0.21	
18	0.0504	9.79	0.021794	0.21	
19	0.0513	9.96	0.022283	0.22	
20	0.0522	10.13	0.022148	0.22	
21	0.0531	10.31	0.023824	0.25	
22	0.0541	10.49	0.026814	0.28	
23	0.0550	10.67	0.045247	0.48	
24	0.0560	10.86	0.116742	1.27	
25	0.0569	11.05	0.246061	2.72	
26	0.0579	11.24	0.100134	1.13	
27	0.0590	11.44	0.045644	0.52	
28	0.0600	11.64	0.023176	0.27	
29	0.0610	11.84	0.014775	0.17	
30	0.0621	12.05	0.010804	0.13	
31	0.0632	12.26	0.008386	0.10	
32	0.0643	12.48	0.006822	0.09	
33	0.0654	12.69	0.004779	0.06	
34	0.0666	12.92	0.003829	0.05	
35	0.0678	13.15	0.003329	0.04	
36	0.0690	13.38	0.004467	0.06	
37	0.0702	13.61	0.005607	0.08	
38	0.0714	13.85	0.004706	0.07	
39	0.0727	14.10	0.003069	0.04	
40	0.0740	14.35	0.002631	0.04	
41	0.0753	14.60	0.000709	0.01	
42	0.0766	14.86	0.000977	0.01	
43	0.0780	15.12	0.000000	0.00	
44	0.0793	15.39	0.000000	0.00	
45	0.0808	15.67	0.000000	0.00	
46	0.0822	15.95	0.000000	0.00	
47	0.0837	16.23	0.000000	0.00	
48	0.0852	16.52	0.000000	0.00	

Probable Future Repair Cost for EX	Probable Decision Point Repair Cost for EX	Probable Total Repair Cost for EX
$10.54	$0.00	$10.54

The big difference between the Total Repair Cost for Exempting versus the Total Repair Cost for the Normal I/M Process is that in the Exempting case, vehicles tend to return 48 months instead of 24 months after their previous-cycle ASM inspection. If the vehicle is not exempted, the Normal I/M Process repair costs are estimated by weighting the monthly probable repair costs by the brown ΔCprobs as shown in Table 4-11, which peak 24 months after the previous-cycle ASM. If the vehicle is exempted, the repair costs are estimated by weighting the monthly probable repair costs by the pink ΔCprobs as shown in Table 4-12, which peak 48 months after the previous-cycle ASM.

Consequently, when exempted vehicles do return for their next-cycle ASM inspection, their failure probabilities are substantially higher and, therefore, the repair costs are higher than if they had remained in the Normal I/M Process. Therefore, the Total Repair Costs for Exempting are higher than the Total Repair Costs for the Normal I/M Process. For this example calculation, the Total Repair Costs for Exempting are $10.54 and for the Normal I/M Process are $7.78. The reason for this is that the exempted vehicle would have degraded an average of 24 months longer than it would have if it had remained in the Normal I/M Process.[33]

Repair Costs for Directing – As with the Normal I/M Process and Exempting, Directing does not incur a Decision Point Repair Cost. In the case of Directing, candidate vehicles are directed to high-performing stations instead of being allowed to get inspected at average I/M stations. In this analysis we have used the report that the fail rate at average stations is 80% of the fail rate at high-performing stations to conclude that directed vehicles are 20% more likely to fail at a high-performing station than at an average station. Accordingly, the probable Future Repair Cost for a vehicle is 20% higher for Directing than for the Normal I/M Process. Thus, we simply multiply the Normal I/M Process probable Total Repair Cost of $7.78 by 1.2 to get the Directing probable Total Repair Cost of $9.34.

Repair Costs for Calling-In – To help demonstrate the effects of Calling-In strategies on repair costs, we use a different set of conditions for the example than we did for Exempting. Table 4-13 shows the example conditions. In this case, the vehicle is a high-emitting vehicle that was previously inspected 12 months before the Decision Point. The previous-cycle results show a fail for NX2525 and a very high RSD measurement for NX. The plot in Figure 4-40 shows a failure probability at the Decision Point, which is in Month 0, of 0.4533. This vehicle is clearly one that might benefit from being called-in off-cycle.

[33] If the Normal I/M Process repair cost were calculated over the same calendar period as the Exempting repair cost, we estimate that the Normal I/M Process repair cost would be slightly higher than the Exempting repair cost.

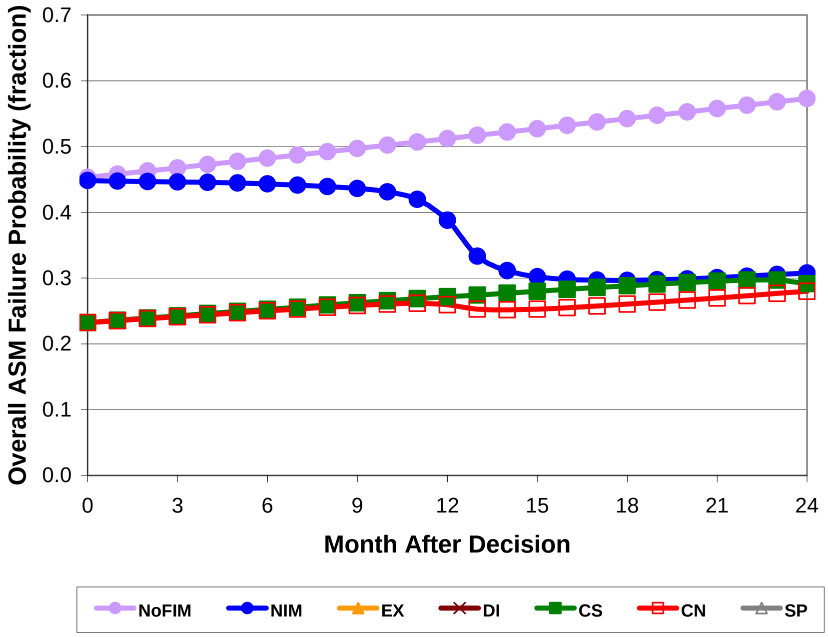
Table 4-13. Simulation Conditions for the High-Emitting Example Vehicle

Vehicle:	1988 Ford Car 3.0L V6 FNTE
Monthly VMT:	1,000 miles
Previous-Cycle ASM Results:	
HC2525	Pass
CO2525	Pass
NX2525	Fail
HC5015	Pass
CO5015	Pass
NX5015	Pass
Time Information:	
Current Date:	03/13/03
Months Since Previous Cycle:	12
Recent RSD Measurements:	
HC	-466.7 ppm
CO	-0.3%
NX	7,763.4 ppm
Future ASM Cutpoints:	
HC2525:	93 ppm
HC5015:	118 ppm
CO2525:	0.64%
CO5015:	0.76%
NX2525:	738 ppm
NX5015:	799 ppm

The curves in Figure 4-40 show the linear increase in overall ASM failure probability for NoFIM if the vehicle would no longer participate in the I/M program. The blue curve shows the effect of the Normal I/M Process with a substantial drop in failure probability around Month 12, which is 24 months after the previous-cycle ASM test. The bottom two curves show the projected failure probability for two different Calling-In options. The curve with the red open squares is for Calling-In No-Sticker where the vehicle is called-in in Month 0, tested, and repaired if needed but must continue on the regular I/M schedule. This means that, in this case, the vehicle must return for its regular I/M inspection around Month 12. The other Calling-In alternative is Calling-In Sticker, which is shown in Figure 4-40 with the green solid squares. In this case after meeting the Call-in ASM requirements in Month 0, the vehicle is given a new 24 month certification. It would, therefore, return for its next I/M inspection around Month 24.

Figure 4-40 also shows a large drop in failure probability at Month 0 from the value of 0.4533 for the Normal I/M Process to a value of 0.2291 for both Calling-In options. This drop in failure probability is a consequence of the call-in ASM inspection performed at the Decision Point. The sample calculations of repair costs for Calling-In No-Sticker and Calling-In Sticker are shown in Tables 4-14 and 4-15.

Figure 4-40. Forecasted Failure Probabilities for the High-Emitting Vehicle for Calling-In Sticker and Calling-In No-Sticker



/bigrig/DecisionModel/IMsimulator/IMsimulator_v03c_CprobCont_repcosts.xls

If vehicles are called in for off-cycle call-in ASM inspections, they would be required to be repaired if they fail the call-in ASM test. Accordingly, for both Calling-In No-Sticker and Calling-In Sticker, there is a possible repair cost at the Decision Point. The probable repair cost is the unit repair cost of $194 times the probability of failure at the Decision Point. This probability is based on the previous-cycle ASM inspection result and the time since the previous cycle.[34] For the vehicle in this calculation example, this produces a probable Decision Point Repair Cost of $87.94 as shown in Tables 4-14 and 4-15.

[34] These failure probabilities are taken from the same calculations described earlier for the calculation of failed miles driven. For example, the failure probability for a vehicle coming in for a call-in ASM test in Month 0 for the Calling-In No-Sticker and Calling-In Sticker are given in Tables 4-4 and 4-5 in Column L in the cell where Y=0. (The values in Table 4-14 and 4-15 are different from the values in Table 4-4 and 4-5 because the vehicle conditions are different.)

Table 4-14. Sample Calculation of Repair Costs for Calling-In No-Sticker

Month	Fprob	Probable Repair Cost If the Vehicle Gets Inspected In the Indicated Month ($)	Likelihood that the Vehicle Will Get an Inspection In the Indicated Month (Brown ΔCprob)	Likely Future Repair Cost Incurred In a Given Month ($)	Probable Decision Point Repair Cost for CN ($)	
Decision Point	0.4533				$87.94	
0	0.2291	44.45	0.0219	0.97		
1	0.2325	45.11	0.0262	1.18		
2	0.2360	45.77	0.0233	1.07		
3	0.2394	46.44	0.0227	1.05		
4	0.2429	47.12	0.0231	1.09		
5	0.2464	47.81	0.0240	1.15		
6	0.2500	48.50	0.0251	1.22		
7	0.2536	49.20	0.0261	1.28		
8	0.2572	49.90	0.0280	1.40		
9	0.2609	50.62	0.0309	1.56		
10	0.2646	51.34	0.0378	1.94		
11	0.2684	52.07	0.0628	3.27		
12	0.2722	52.81	0.1376	7.26		
13	0.2760	53.55	0.2231	11.95		
14	0.2799	54.30	0.0981	5.32		
15	0.2838	55.06	0.0487	2.68		
16	0.2878	55.83	0.0283	1.58		
17	0.2918	56.61	0.0185	1.05		
18	0.2958	57.39	0.0148	0.85		
19	0.2999	58.18	0.0113	0.66		
20	0.3040	58.98	0.0090	0.53		
21	0.3082	59.78	0.0068	0.41		
22	0.3124	60.60	0.0057	0.35		
23	0.3166	61.42	0.0049	0.30		
24	0.3209	62.25	0.0063	0.39		
25	0.3252	63.09	0.0072	0.45		
26	0.3296	63.93	0.0052	0.33		
27	0.3339	64.79	0.0045	0.29		
28	0.3384	65.65	0.0039	0.26		
29	0.3429	66.52	0.0024	0.16		
30	0.3474	67.39	0.0022	0.15		
31	0.3519	68.28	0.0025	0.17		
32	0.3565	69.17	0.0003	0.02		
33	0.3612	70.07	0.0003	0.02		
34	0.3658	70.97	0.0005	0.04		
35	0.3706	71.89	0.0005	0.04		
36	0.3753	72.81	0.0001	0.01		
37	0.3801	73.74	0.0018	0.13		
38	0.3849	74.68	0.0018	0.13		
39	0.3898	75.62	0.0009	0.07		
40	0.3947	76.58	0.0007	0.05		
41	0.3997	77.54	0.0000	0.00		
42	0.4047	78.50	0.0000	0.00		
43	0.4097	79.48	0.0000	0.00		
44	0.4147	80.46	0.0000	0.00		
45	0.4198	81.45	0.0000	0.00		
46	0.4250	82.44	0.0000	0.00		
47	0.4301	83.45	0.0000	0.00		
48	0.4353	84.45	0.0000	0.00		
				Probable Future Repair Cost for CN	**Probable Decision Point Repair Cost for CN**	**Probable Total Repair Cost for CN**
				$52.85	$87.94	$140.80

Table 4-15. Sample Calculation of Repair Costs for Calling-In Sticker

Month	Fprob	Probable Repair Cost If the Vehicle Gets Inspected In the Indicated Month ($)	Likelihood that the Vehicle Will Get an Inspection In the Indicated Month (Pink ΔCprob)	Likely Future Repair Cost Incurred In a Given Month ($)	Probable Decision Point Repair Cost for CS ($)	
Decision Point	0.4533				$87.94	
0	0.2291	44.45	0.0012	0.06		
1	0.2325	45.11	0.0026	0.12		
2	0.2360	45.77	0.0032	0.14		
3	0.2394	46.44	0.0054	0.25		
4	0.2429	47.12	0.0091	0.43		
5	0.2464	47.81	0.0103	0.49		
6	0.2500	48.50	0.0115	0.56		
7	0.2536	49.20	0.0122	0.60		
8	0.2572	49.90	0.0122	0.61		
9	0.2609	50.62	0.0126	0.64		
10	0.2646	51.34	0.0141	0.72		
11	0.2684	52.07	0.0160	0.83		
12	0.2722	52.81	0.0196	1.03		
13	0.2760	53.55	0.0234	1.26		
14	0.2799	54.30	0.0208	1.13		
15	0.2838	55.06	0.0203	1.12		
16	0.2878	55.83	0.0207	1.15		
17	0.2918	56.61	0.0215	1.22		
18	0.2958	57.39	0.0225	1.29		
19	0.2999	58.18	0.0233	1.36		
20	0.3040	58.98	0.0251	1.48		
21	0.3082	59.78	0.0276	1.65		
22	0.3124	60.60	0.0338	2.05		
23	0.3166	61.42	0.0562	3.45		
24	0.3209	62.25	0.1230	7.66		
25	0.3252	63.09	0.1996	12.59		
26	0.3296	63.93	0.0877	5.61		
27	0.3339	64.79	0.0435	2.82		
28	0.3384	65.65	0.0253	1.66		
29	0.3429	66.52	0.0165	1.10		
30	0.3474	67.39	0.0132	0.89		
31	0.3519	68.28	0.0101	0.69		
32	0.3565	69.17	0.0081	0.56		
33	0.3612	70.07	0.0061	0.43		
34	0.3658	70.97	0.0051	0.36		
35	0.3706	71.89	0.0044	0.32		
36	0.3753	72.81	0.0056	0.41		
37	0.3801	73.74	0.0064	0.47		
38	0.3849	74.68	0.0046	0.35		
39	0.3898	75.62	0.0041	0.31		
40	0.3947	76.58	0.0035	0.27		
41	0.3997	77.54	0.0021	0.16		
42	0.4047	78.50	0.0020	0.16		
43	0.4097	79.48	0.0022	0.18		
44	0.4147	80.46	0.0003	0.02		
45	0.4198	81.45	0.0003	0.02		
46	0.4250	82.44	0.0005	0.04		
47	0.4301	83.45	0.0005	0.04		
48	0.4353	84.45	0.0001	0.01		
				Probable Future Repair Cost for CS	**Probable Decision Point Repair Cost for CS**	**Probable Total Repair Cost for CS**
				$60.75	$87.94	$148.69

The probable Future Repair Cost in the 48 months after the Decision Point is based on the monthly probable costs weighted by the probability that the vehicle will receive its next-cycle ASM inspection in a given month. In the case of both Calling-In No-Sticker and Calling-In Sticker, the monthly failure probabilities are the same, as shown in Column 2 of Tables 4-14 and 4-15. Rather than being based on the previous-cycle ASM results as for the Normal I/M Process, Directing, and Exempting, future failure probabilities for Calling-In (and Scrapping) strategies are based on the result of the call-in ASM test in Month 0 and the time since the call-in ASM test.[35] The reason for this difference is that for Calling-In and Scrapping, the ASM test at the Decision Point is the most recent ASM test, which, of course, is a better indicator of future failure probability than any earlier ASM test.

The weighting factors used for the monthly probable repair costs for Calling-In differ between Sticker and No-Sticker. In the case of Calling-In No-Sticker, even though vehicles are called in and receive an ASM, they are still required to follow their Normal I/M Process schedule and to be inspected at a regular I/M station approximately 24 months after their previous-cycle ASM inspection. Therefore, for the purposes of calculating the probable Future Repair Costs of Calling-In No-Sticker, the monthly probable costs are weighted by the brown ΔCprobs, which have peak probabilities around 24 months after the previous-cycle ASM, which for the example is around Month 12 as shown in Table 4-14. In the case of Calling-In Sticker, vehicles would receive a new certification at the Decision Point after meeting the usual I/M program requirements. In this case, the pink ΔCprobs would be used as the weighting factors for the monthly probable repair costs. The pink ΔCprobs have peak probabilities around 24 months after the call-in ASM test, which for the example is around Month 24 as shown in Table 4-15.

Tables 4-14 and 4-15 show that the probable Future Repair Costs for the example vehicle for Calling-In No-Sticker and Calling-In Sticker are \$52.85 and \$60.75. When we add in the probable Decision Point Repair Cost of \$87.94 for each, the probable Total Repair Costs for this example for Calling-In No-Sticker and Calling-In Sticker are \$140.80 and \$148.69, respectively.

The repair costs for Sticker will always be slightly larger than for No-Sticker. The reason for this is that for Calling-In Sticker a new certification is given at the call-in test, and this delays the date of the next-cycle inspection. In this example, the next-cycle inspection for the Calling-In No-Sticker path would be around Month 12, while the next-cycle inspection for the Calling-In

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[35] These failure probabilities are taken from the same calculations described earlier for the calculation of failed miles driven. For example, the failure probability for a vehicle coming in for an I/M program ASM test in Month 4 for Calling-In No-Sticker and Calling-In Sticker are given in Tables 4-4 and 4-5 in Column N in the cell just above the thick black line, where Y=3. (The values in Tables 4-14 and 4-15 are different from the values in Tables 4-4 and 4-5 because the vehicle conditions are different.)

Sticker path would be around Month 24 – a delay of 12 months. This delay allows the failure probability for Calling-In Sticker to go higher than it would have for Calling-In No-Sticker. Therefore, the repair cost for Calling-In Sticker is higher than for Calling-In No-Sticker.

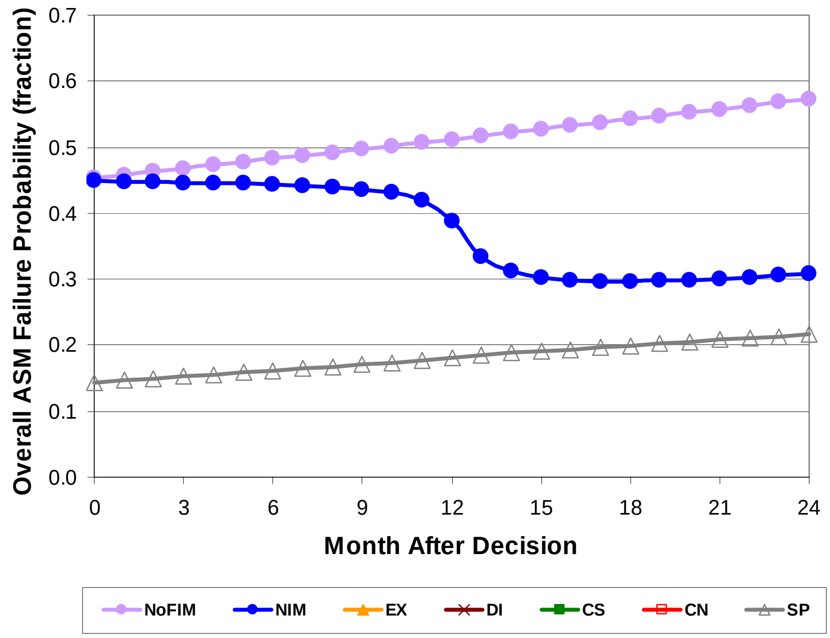
The Total Repair Costs for the Calling-In strategies need to be compared with the Total Repair Cost for leaving this vehicle in the Normal I/M Process. This cost is calculated by the same method as described above for the Normal I/M Process but using the conditions from Table 4-13. However, since this vehicle is high emitting and has a different I/M history, the Normal I/M Process probable Total Repair Cost is the much higher $98.32. Thus, both Calling-In options have substantially higher repair costs than leaving the vehicle in the Normal I/M Process.

Both Calling-In strategies will always be associated with increased Total Repair Costs relative to the Normal I/M Process. The reason for this is that the call-in ASM test is an “extra” test relative to the Normal I/M Process. This extra test represents an extra opportunity to incur repair costs.

Repair Costs for Scrapping – Scrapping candidates are the same sort of candidates as those for Calling-In – high-emitting vehicles in mid-cycle. Figure 4-41 shows the situation for the same vehicle that was described in Table 4-13. However, Figure 4-41 shows the failure probability curve for Scrapping instead of for Calling-In Sticker and Calling-In No-Sticker. In this situation, the contemplated alternative to the Normal I/M Process is to call the vehicle in for a scrappage ASM in Month 0. If the vehicle would fail the scrappage ASM, it would be scrapped and not repaired. Therefore, the Decision Point repair cost for Scrapping is zero whether it passes or fails the scrappage ASM test. Figure 4-41 shows the future Scrapping failure probabilities as the lowest curve with the gray open triangles. The failure probability curve is derived from the chance that the vehicle would pass the scrappage ASM at the Decision Point since, if the vehicle failed the scrappage ASM at the Decision Point, it would be scrapped and its future failure probability would, therefore, be zero through the entire period. The calculation of repair costs for the Scrapping strategy for this vehicle is shown in Table 4-16.

Just as for the Normal I/M Process, Exempting, and Directing, in the case of Scrapping, there is no Decision Point Repair Cost incurred because if a vehicle fails the scrappage ASM test at the Decision Point, it is scrapped rather than being repaired. All of the probable Future Repair Costs come from the chance that the vehicle passes the scrappage ASM test and is then later repaired as it proceeds through the I/M program.

Figure 4-41. Forecasted Failure Probabilities for the High-Emitting Vehicle for Scrapping



/bigrig/DecisionModel/IMsimulator/IMsimulator_v03c_CprobCont_repcosts.xls

For the case of Scrapping, repair costs are reduced with respect to the Normal I/M Process because after Scrapping occurs, a vehicle that would pass a scrappage ASM test would be more likely to be a low-emitting vehicle. Nevertheless, such vehicles still have a probability of failing the next regular ASM test. They would possibly require repairs as they pass through the I/M program in the 48 months after the Decision Point and therefore would incur Future Repair Costs. Of course, the vehicles that are scrapped would incur no Future Repair Costs.

In the Scrapping scenario analyzed in this study, we assumed that vehicles that failed the scrapping ASM test would be scrapped and those that passed would continue through the I/M program on a schedule determined by their existing previous-cycle certification. The monthly probable repair costs of the vehicles that passed the scrapping ASM test would be substantially lower than the monthly probable repair costs of the vehicles that failed the scrappage ASM test if they had not been scrapped. The probable Future Repair Cost of the scrappage-ASM-passing vehicles is determined by the sum of the unit repair cost of $194 times the monthly failure probability[36] of the scrappage-ASM-passing vehicles weighted by the brown ΔCprobs, as shown

[36] These failure probabilities are taken from calculations similar to those described earlier for the calculation of probable FTP emissions. For example, the FTP emisssions for a vehicle coming in for an I/M program ASM test in Month 4 for Scrapping is given in Table 4-7 in Column N in the cell just above the thick black line, where Y=3. The failure probability for that cell can be calculated using a table similar to Table 4-7.

in Table 4-16, which are the probabilities that the vehicle will be inspected in a given month based on the previous-cycle ASM test. These probabilities peak at 24 months after the previous-cycle ASM test.

The probable Total Repair Cost for a vehicle that is targeted for Scrapping should always be less than the probable Total Repair Cost for the vehicle if it had stayed in the Normal I/M Process. Table 4-16 shows that the probable Total Repair Cost for deciding on the Scrapping path for this vehicle is \$32.85. This repair cost is substantially lower than the repair cost of \$98.32 if the vehicle would stay in the Normal I/M Process.

Table 4-16. Sample Calculation of Repair Costs for Scrapping

Month	Fprob	Probable Repair Cost If the Vehicle Gets Inspected In the Indicated Month ($)	Likelihood that the Vehicle Will Get an Inspection In the Indicated Month (Brown ΔCprob)	Likely Future Repair Cost Incurred In a Given Month ($)	Probable Decision Point Repair Cost for SP ($)
Decision Point	0.4533				$0.00
0	0.1402	27.20	0.0219	0.59	
1	0.1426	27.67	0.0262	0.73	
2	0.1450	28.13	0.0233	0.66	
3	0.1474	28.59	0.0227	0.65	
4	0.1498	29.06	0.0231	0.67	
5	0.1522	29.53	0.0240	0.71	
6	0.1547	30.00	0.0251	0.75	
7	0.1571	30.48	0.0261	0.79	
8	0.1596	30.96	0.0280	0.87	
9	0.1620	31.43	0.0309	0.97	
10	0.1645	31.91	0.0378	1.21	
11	0.1670	32.40	0.0628	2.04	
12	0.1695	32.88	0.1376	4.52	
13	0.1720	33.36	0.2231	7.44	
14	0.1745	33.85	0.0981	3.32	
15	0.1770	34.34	0.0487	1.67	
16	0.1795	34.83	0.0283	0.99	
17	0.1820	35.32	0.0185	0.65	
18	0.1846	35.81	0.0148	0.53	
19	0.1871	36.30	0.0113	0.41	
20	0.1896	36.79	0.0090	0.33	
21	0.1922	37.28	0.0068	0.25	
22	0.1947	37.77	0.0057	0.22	
23	0.1973	38.27	0.0049	0.19	
24	0.1998	38.76	0.0063	0.24	
25	0.2023	39.25	0.0072	0.28	
26	0.2049	39.75	0.0052	0.21	
27	0.2074	40.24	0.0045	0.18	
28	0.2100	40.73	0.0039	0.16	
29	0.2125	41.23	0.0024	0.10	
30	0.2150	41.72	0.0022	0.09	
31	0.2176	42.21	0.0025	0.11	
32	0.2201	42.70	0.0003	0.01	
33	0.2226	43.19	0.0003	0.01	
34	0.2251	43.68	0.0005	0.02	
35	0.2276	44.16	0.0005	0.02	
36	0.2302	44.65	0.0001	0.00	
37	0.2326	45.13	0.0018	0.08	
38	0.2351	45.62	0.0018	0.08	
39	0.2376	46.10	0.0009	0.04	
40	0.2401	46.58	0.0007	0.03	
41	0.2425	47.05	0.0000	0.00	
42	0.2450	47.53	0.0000	0.00	
43	0.2474	48.00	0.0000	0.00	
44	0.2498	48.47	0.0000	0.00	
45	0.2523	48.94	0.0000	0.00	
46	0.2547	49.40	0.0000	0.00	
47	0.2570	49.86	0.0000	0.00	
48	0.2594	50.32	0.0000	0.00	

Probable Future Repair Cost for SP	Probable Decision Point Repair Cost for SP	Probable Total Repair Cost for SP
$32.85	$0.00	$32.85

5.0 Approach for Evaluating Vehicle Rankings

In the previous section, vehicles were ranked in 35 different ways to provide information for evaluating the benefits of using different failure probability models and different ranking criteria. Table 4-8 categorized these 35 different vehicle rankings for the four main questions in this analysis with respect to Directing, Exempting, Calling-in, and Scrapping.

RSD researchers typically rank vehicles based on RSD measurements. We would like to compare the performances of vehicle rankings developed in this study with those that would be used by RSD researchers. Accordingly, in this section we will compare the benefits of ranking by the three raw RSD concentration measurements, RSD HC, RSD CO, and RSD NX, with the benefits of ranking by the other 32 methods.

In this section, the benefits to the fleet for each of the 35 rankings are estimated so that the advantages, disadvantages, and trade-offs of the different failure probability models and their inputs and the different ranking criteria can be quantified. Section 5.1 defines the two types of fleet benefits that will be used in the evaluation. Section 5.2 describes the method for estimating monthly failure probabilities and FTP emissions for the individual vehicles in the analysis dataset. Section 5.3 shows how these individual vehicle values are combined to produce the estimates of fleetwide benefits for different fleet targeting percentages. Finally, Section 5.4 shows the fleet benefit results of the rankings of the pilot dataset. The fleet benefits presented in Section 5.4 will be used in a subsequent report to evaluate implementation strategies.

5.1 Criteria for Evaluating Fleet Benefits for Vehicle Rankings

Whether the intervention activity is Directing, Exempting, Calling-in, or Scrapping, the goal of the effort is to produce an improvement relative to the Normal I/M Process. However, we need to have definable quantities that can be calculated and that represent recognized goals of the I/M program so that the 35 vehicle rankings can be evaluated using the pilot dataset.

What is the goal of the California I/M program? We may be presumptuous here in attempting to answer this question; however, we need to answer it so that we can develop measures of fleet benefits. California would like to minimize the total mass emissions from its vehicles. The program tries to achieve this goal by testing vehicles biennially using the ASM tailpipe emissions concentration test administered at I/M program stations. In this implementation strategy, vehicles pass or fail the emissions test by comparing the test results with a table of ASM cutpoints. While the I/M program requires vehicles to be tested at least on a biennially basis, they would like to have all fleet vehicles pass an ASM test whenever the vehicle might be called in. Further, it makes sense that the I/M program would be more concerned with vehicles that drive more miles each month than vehicles that are driven very little. We have discussed these ideas earlier in the report. They lead to the notion of minimizing the fleet's total failed miles driven over one biennial cycle.

Because of the way the I/M program is implemented, that is, by determining whether a vehicle passes or fails an emissions test, the California I/M program addresses the higher goal of reducing tailpipe emissions by trying to ensure that all vehicles pass their respective ASM cutpoints. We could say that the implementation goal of the program is to ensure that all vehicles pass their ASM cutpoints during their regular I/M inspections. This means that the important connection between the lower goal of passing emissions inspections and the higher goal of reducing emissions is achieved through the cutpoints. Consequently, setting proper cutpoints is one of the critical factors in the I/M program.

In its current implementation, therefore, the I/M program makes no distinction between the size of the excess emissions for two different vehicles. That is, it is only whether the vehicles pass or fail that is important to the I/M program – as it is currently set up. For example, consider two vehicles. One vehicle is a five-year-old vehicle and it has quite low ASM cutpoints. The other vehicle is a 20-year-old vehicle and because it does not have as highly developed emission control technology as the first vehicle, the ASM cutpoints for the second vehicle are much higher. If both vehicles have an emission control system component failure, the excess emissions of the two vehicles (measured tailpipe emissions minus ASM tailpipe cutpoint) will not be the same. It is possible that the excess emissions of the newer vehicle will be smaller than those of the older vehicle since the emission control system components of the first vehicle that do not fail may help keep the tailpipe emissions concentrations from going very high. In any case, from the point of view of the I/M program, both vehicles are simply failed which is a strategy that does not take into account the size of the excess emissions of the two vehicles.

The above example demonstrates that the I/M program in its current implementation does not "care" about the size of the excess emissions. Accordingly, to be consistent with this reality, the first measure of benefit to be described is the change in failed miles driven (ΔFMD) by the vehicles in the fleet for the 35 different vehicle rankings. ΔFMD is calculated as the difference between the failed miles driven for the Normal I/M Process and the failed miles driven for Directing, Exempting, Calling-in, or Scrapping using a particular model and ranking criterion.

Just because the defacto implementation in the I/M program is based on passes and fails, it does not mean that the total tailpipe emissions of the fleet are unimportant. Reduction of the total tailpipe emissions of the fleet is the higher goal of the I/M program. Therefore, in this analysis, we need to include a measure of the change in total tailpipe emissions that is produced by Directing, Exempting, Calling-in, and Scrapping intervention strategies versus the Normal I/M Process. The quantities that we calculate to evaluate these fleetwide emissions are the change in FTP mass emissions (ΔFTP) of the fleet over the 24 months after the decision point. These changes in FTP emissions are calculated by considering the FTP emissions for the Normal I/M Process and the FTP emissions for Directing, Exempting, Calling-in, or Scrapping.

While the fraction of the targeted vehicles that fail at the decision point is not a benefit, it is nevertheless an important quantity that needs to be considered when evaluating a vehicle ranking. Because vehicle rankings that would produce low vehicle failure fractions at the decision point test would be less favored even if the rankings targeted vehicles with large likely ΔFMD or ΔFTP, the fraction failing at the decision point needs to be considered. It is important to understand that ΔFMD and ΔFTP already include the influences of the probability of individual vehicles failing at the decision point.

All the models developed for this analysis were built to predict the ASM failure probability of emissions tests performed on vehicles when vehicle owners knew in advance that their vehicles would be tested. We know that owners may perform pre-inspection repairs before taking their vehicles to an I/M station for its inspection. This is a legitimate activity and helps reduce the emissions of the fleet. However, because of pre-inspection repairs, the data recorded in the VID tends to indicate that vehicles are in a better state of repair than they actually are during the two years between biennial I/M program inspections. As a consequence, in general, the ASM failure probabilities calculated by the models and the estimated ASM emissions and FTP emissions that are calculated for individual vehicles from those models are expected to be lower than on-road values. California's program of roadside pullovers, in which vehicles are given immediate unannounced ASM emissions tests on the roadside, confirm that ASM fail rates for unannounced tests are higher than fail rates for I/M station tests.

The known differences of ASM failure rates and FTP emission rates between I/M station tests and roadside pullover tests means that the benefits calculated in this analysis for ΔFMD and ΔFTP are probably lower than the actual benefits for on-road vehicles. We believe that estimates of the benefits to ΔFMD and ΔFTP for on-road vehicle status could be performed in a subsequent study using existing roadside ASM pullover data.

In spite of the differences that exist between I/M station emissions and failure rates and on-the-road emissions and failure rates, we believe that the vehicle rankings will be relatively independent of these differences. However, the ΔFMD and ΔFTP benefits calculated in this analysis will probably be biased low.

5.2 Estimating Failed Miles Driven and FTP Mass Emissions for Individual Vehicles

Before we can estimate the fleet benefits of different vehicle rankings, we need to know the failed miles driven and the FTP mass emissions of all 69,629 vehicles in the pilot dataset for each of the 24 months after the decision point, which in the study corresponds to the date of the RSD measurement. The problem is that we do not have any measured values for these quantities. We do not have any measurements of ASM failures at the decision point, failed miles driven, or FTP mass emissions for individual vehicles for each of the 24 months after Directing, Exempting, Calling-in, or Scrapping decisions since we did not actually interrupt the usage of any vehicle with a special ASM test. In this study, we observed only the ASM pass/fail result of the vehicles whenever they participated in the Normal I/M Process.

During the planning for the project, we made a conscious decision to simply allow vehicles to get their ASM inspections by following their "natural" behavior. Even if we had called-in the vehicles after remote sensing to receive Directing, Exempting, Calling-in, or Scrappage ASM tests, those tests would only provide the fail rate of the targeted vehicles at the decision point. We would still not have the future failed miles driven and FTP emissions for each of the 24 months after the decision point as a result of the decision point test and potential repair. There were two primary reasons why we decided not to call vehicles in for ASM tests. First, at the time of field testing we had no models and, therefore, no basis for choosing vehicles for Directing, Exempting, Calling-in, or Scrappage ASM tests. Second, since the ASM test that would follow the special ASM test would be obtained by a natural I/M process, where the vehicle owner brings in his vehicle for the regularly scheduled inspection, monthly ASM inspections of the vehicles in the dataset would not be obtained. In addition, the natural ASM inspections would not be abundant enough to estimate the ΔFMD for the pilot dataset very well.

As a consequence, the ASM fail rate at the decision point, failed miles driven, and FTP mass emissions for individual vehicles in the dataset for each of the 24 months after a simulated Directing, Exempting, Calling-in No Sticker, Calling-in Sticker, Scrappage, and Normal I/M Process are estimated using the models developed in the study. Models C and D were used to estimate these expected values. Only these two models have time-dependent outputs of failure probability and FTP emissions. The methods of calculation for the values of FMD and FTP for individual vehicles by Models C and D for Directing, Exempting, Calling-in No Sticker, Calling-in Sticker, Scrappage, and the Normal I/M Process have already been presented in Section 4.2. The calculations are made by Core.sas.

5.3 Calculating Evaluation Criteria for Vehicle Rankings

The previous subsection described how to calculate the potential ΔFMD and ΔFTP for individual vehicles over the 24 months after the decision point. We use the values calculated from Models C or D as an estimate of the truth. In this subsection, we describe how these individual vehicle estimates are combined to provide an estimate of ΔFMD and ΔFTP for the fleet over the 24 months after each individual vehicle's decision point. The results of these calculations are also dependent on the percent of the fleet that is targeted for each individual question. Clearly, if zero percent of the fleet is targeted, the benefits (ΔFMD and ΔFTP) are equal to zero because all vehicles would be simply following the Normal I/M Process.

The idea of targeting is to select those vehicles for intervention in the Normal I/M Process that would produce the largest benefit to the I/M program. In the calculations to estimate fleet benefits we use a process that we call slicing. In slicing, we rank all of the vehicles by the vehicle ranking under consideration and then add up the benefits that are expected for the highest ranked vehicles. The number of vehicles in this top "slice" divided by the total number of vehicles in the dataset is the fleet targeting percentage. Only the vehicles in the top slice would have their normal I/M process interrupted by a special strategy. Therefore, any benefits to be realized could only come from the vehicles in the top slice. For all vehicles in the bottom, the ΔFMD and ΔFTP would be zero since they would all be following the Normal I/M Process.

First, we describe how the evaluation criteria for the fleet are calculated. Then, we provide a simplified example of these calculations. Each of the evaluation criteria are calculated as described below:

- **ΔFMD of the fleet over 24 months (%ΔFMD)** – Add up the ΔFMD over 24 months for the targeted vehicles and divide by the Normal I/M Process FMD over 24 months for all for the vehicles in the fleet. This will be the change in FMD for the fleet that is produced by treating only the targeted vehicles and is expressed as a percent of the entire fleet's failed miles driven over 24 months for the Normal I/M Process. Vehicles that are not targeted will not contribute to %ΔFMD.
- **ΔFTP of the fleet over 24 months (%ΔFTP)** – Add up the ΔFTP over 24 months for the targeted vehicles and divide by the Normal I/M Process FTP emissions over 24 months for all of the vehicles in the fleet. This will be the change in estimated FTP for the fleet that is produced by treating only the targeted vehicles

and is expressed as a percent of the entire fleet's FTP mass emission over 24 months for the Normal I/M Process. Vehicles that are not targeted will not contribute to %ΔFTP. The values for %ΔFTP of the fleet are calculated separately for FTP HC, CO, and NX.

- **Fail fraction at the decision point** – Add up the overall ASM Fprobs of the individual targeted vehicles at the decision point and divide by the number of targeted vehicles. This will be the fraction of the targeted vehicles that are expected to fail the ASM test at the decision point.

Before we present the results of the analysis on the full dataset, we will demonstrate how the evaluation calculations are performed with a 100-vehicle example. We selected 100 vehicles from the dataset to form a small dataset that could be used to see all of the calculations in an evaluation.

Table 5-1 shows the results of a Calling-In No-Sticker evaluation calculated on a vehicle ranking provided by the Model B ASM failure probability at decision point. Model B is the model that uses vehicle description alone. Column A gives the Model B values. Column A shows that vehicles are ranked in a descending order from the highest Model B failure probability of 0.2432 to the lowest of 0.0000. Column B gives a vehicle ranking number from 1 through 100 for each of the vehicles in the dataset.

In this example, we want to evaluate the benefits for Calling-In No-Sticker targeting that would be achieved by ranking the 100 vehicles using the Model B decision point failure probability. As discussed previously, because no vehicles were actually called in and repaired, the monthly failure probabilities, failed miles driven, and FTP emissions that would have occurred after call-ins and repairs must be estimated. In this example, these estimates are provided by Model C for the evaluation. All of the values in Columns C through O are a result of calculations using Model C.

The first part of the evaluation is to determine the fail fraction of the vehicles at the decision point for different fleet targeting percentages. These calculations are shown in Columns C, D, and E. Column C gives the probability that the vehicle would fail a decision point ASM test as calculated by Model C. The general trend in the probabilities for Model C in the table is from high probabilities at the top to low probabilities at the bottom. Nevertheless, there are some large differences between the two probabilities from the two models. For example, for Vehicle 18, the Model B probability, which was used for ranking, is 0.0817 while the Model C probability, which will be used for evaluation, is 0.731 – a difference of more than a factor of eight.

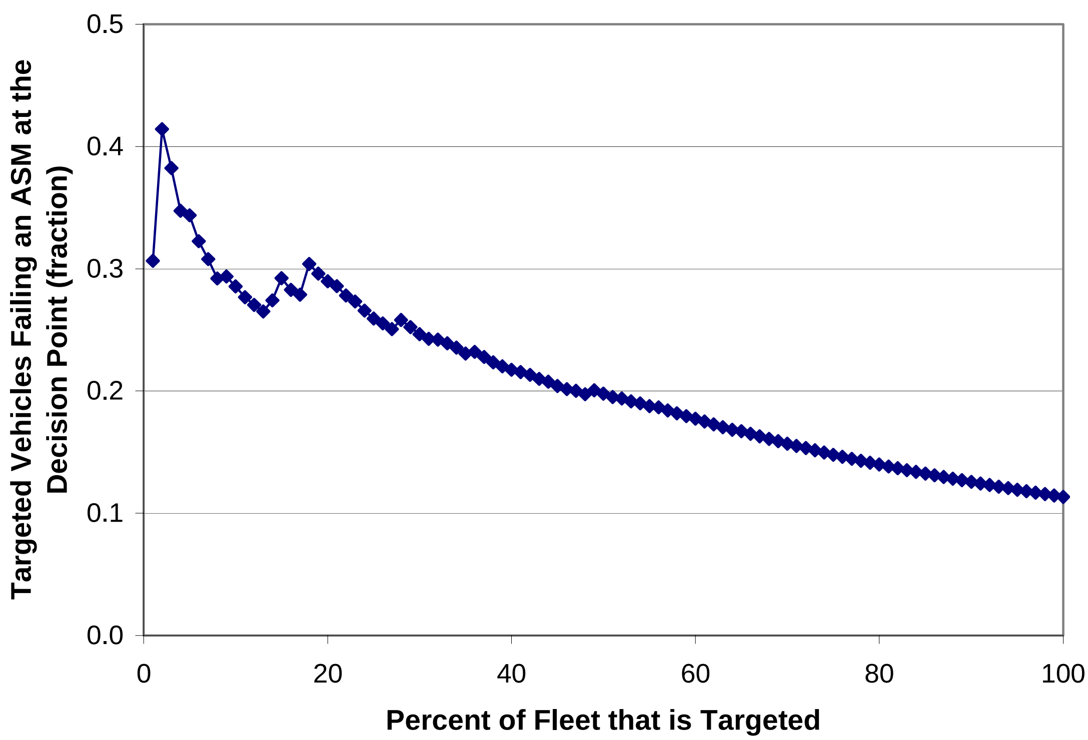
Table 5-1. An Example Model-C Evaluation for a Calling-In No-Sticker 100-Vehicle Ranking

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
Ranked by Model B		**Evaluated by Model C**												
Model B Probability that Vehicle Will Fail an ASM at the Decision Point	**Vehicle Ranking for Calling-In No-Sticker Targeting**	**Probability that Vehicle Will Fail an ASM at the Decision Point**	**Cumulative Sum of the Probabilities that Vehicle Will Fail an ASM at the Decision Point**	**Expected Fraction of Targeted Vehicles That Will Fail an ASM at the Decision Point**	**Expected FMD (miles/24months)**		**Expected ΔFMD (miles/24months)**	**Cumulative Expected ΔFMD (miles/24months)**	**Cumulative Expected %ΔFMD (% of sample total NIM FMD)**	**Expected FTP NX (g/24months)**		**Expected ΔFTP NX (g/24months)**	**Cumulative Expected ΔFTP NX (g/24months)**	**Cumulative Expected %ΔFTP NX (% of sample total NIM FTP NX)**
		If Vehicle is Called In		**If Vehicles in the Top Slice Are Called In**	**If Vehicle Is Called In**	**If Vehicle Remains in the Normal IM Process**	**If Vehicle Is Called In Rather Than Remaining in the Normal IM Process**	**If Vehicles In Top Slice Are Called In**	**If Vehicles In Top Slice Are Called In**	**If Vehicle Is Called In**	**If Vehicle Remains in the Normal IM Process**	**If Vehicle Is Called In Rather Than Remaining in the Normal IM Process**	**If Vehicles In Top Slice Are Called In**	**If Vehicles In Top Slice Are Called In**
0.2432	1	0.306	0.306	0.306	5361	5619	-257	-257	-0.10	33136	34223	-1086	-1086	-0.08
0.2104	2	0.522	0.828	0.414	12017	13143	-1127	-1384	-0.55	20778	20817	-39	-1126	-0.08
0.1869	3	0.319	1.147	0.382	5162	5576	-415	-1799	-0.71	41007	41193	-186	-1311	-0.09
0.1683	4	0.243	1.390	0.347	4027	4161	-134	-1932	-0.76	20793	20999	-205	-1517	-0.10
0.1568	5	0.328	1.718	0.344	6151	6669	-518	-2451	-0.97	26674	27602	-928	-2445	-0.17
0.1482	6	0.218	1.935	0.323	3649	3978	-329	-2780	-1.10	26068	26585	-517	-2962	-0.20
0.1420	7	0.219	2.155	0.308	3611	3922	-311	-3091	-1.22	28552	29415	-863	-3825	-0.26
0.1337	8	0.182	2.337	0.292	3406	3635	-229	-3319	-1.31	24552	25602	-1050	-4874	-0.34
0.1257	9	0.306	2.643	0.294	4921	5581	-660	-3979	-1.57	20198	21528	-1330	-6205	-0.43
0.1181	10	0.212	2.854	0.285	3290	3535	-244	-4223	-1.67	32130	32952	-822	-7027	-0.49
0.1132	11	0.187	3.042	0.277	5956	6006	-50	-4273	-1.69	24932	25068	-136	-7163	-0.50
0.1094	12	0.202	3.244	0.270	3195	4216	-1020	-5293	-2.09	28168	29290	-1122	-8285	-0.57
0.1026	13	0.199	3.444	0.265	4886	5126	-240	-5533	-2.18	15744	16352	-607	-8892	-0.62
0.0991	14	0.393	3.837	0.274	4593	7210	-2617	-8151	-3.22	23765	27005	-3240	-12132	-0.84
0.0942	15	0.545	4.382	0.292	10022	12414	-2392	-10542	-4.16	20046	25129	-5083	-17215	-1.19
0.0873	16	0.141	4.523	0.283	2729	2984	-256	-10798	-4.26	35115	36201	-1086	-18301	-1.27
0.0855	17	0.217	4.740	0.279	4884	5299	-415	-11213	-4.43	17085	17573	-487	-18789	-1.30
0.0817	18	0.731	5.471	0.304	6978	12243	-5265	-16478	-6.51	18787	23960	-5173	-23962	-1.66
0.0759	19	0.151	5.622	0.296	2558	2723	-165	-16643	-6.57	26403	27001	-598	-24559	-1.70
0.0709	20	0.170	5.792	0.290	3309	3508	-199	-16842	-6.65	18300	18800	-500	-25060	-1.73
0.0689	21	0.210	6.002	0.286	2531	3292	-760	-17602	-6.95	20606	23909	-3303	-28363	-1.96
0.0673	22	0.114	6.116	0.278	2437	2659	-223	-17825	-7.04	30865	31647	-782	-29145	-2.02
0.0633	23	0.166	6.282	0.273	3547	3907	-359	-18184	-7.18	17814	18443	-629	-29774	-2.06
0.0621	24	0.097	6.379	0.266	1764	1788	-25	-18209	-7.19	19990	20427	-437	-30211	-2.09
0.0596	25	0.099	6.478	0.259	1991	2140	-149	-18358	-7.25	25095	25738	-643	-30854	-2.14
0.0571	26	0.159	6.637	0.255	4020	4553	-533	-18892	-7.46	17925	18417	-492	-31345	-2.17
0.0540	27	0.126	6.764	0.251	3477	3777	-300	-19191	-7.58	16323	16814	-491	-31836	-2.20
0.0517	28	0.461	7.224	0.258	3556	6917	-3361	-22552	-8.90	12716	14420	-1704	-33540	-2.32
0.0503	29	0.090	7.314	0.252	1912	2017	-106	-22658	-8.94	17075	17452	-377	-33918	-2.35
0.0477	30	0.080	7.395	0.246	1626	1991	-365	-23023	-9.09	22349	23886	-1537	-35454	-2.45
0.0457	31	0.131	7.525	0.243	2683	2906	-223	-23246	-9.18	14301	14635	-334	-35788	-2.48
0.0440	32	0.218	7.744	0.242	5639	5786	-147	-23393	-9.24	16727	16903	-176	-35964	-2.49
0.0421	33	0.143	7.887	0.239	3892	4340	-448	-23841	-9.41	13027	13459	-432	-36396	-2.52
0.0407	34	0.118	8.005	0.235	2927	3221	-294	-24135	-9.53	18476	18907	-431	-36828	-2.55
0.0383	35	0.062	8.067	0.230	2406	2456	-51	-24186	-9.55	23114	23195	-81	-36909	-2.55
0.0369	36	0.284	8.351	0.232	2180	2865	-685	-24871	-9.82	14583	14951	-368	-37277	-2.58
0.0347	37	0.074	8.424	0.228	1378	1481	-103	-24974	-9.86	26854	27523	-669	-37946	-2.63
0.0333	38	0.067	8.492	0.223	1477	1753	-276	-25250	-9.97	19410	20141	-732	-38678	-2.68
0.0319	39	0.095	8.587	0.220	2787	2997	-210	-25461	-10.05	8933	9130	-197	-38875	-2.69
0.0311	40	0.109	8.696	0.217	2534	2748	-214	-25675	-10.14	14116	14480	-364	-39239	-2.72
0.0291	41	0.132	8.829	0.215	5058	5342	-284	-25959	-10.25	10951	11392	-441	-39680	-2.75
0.0272	42	0.120	8.948	0.213	3002	3309	-307	-26266	-10.37	13847	14255	-408	-40088	-2.77
0.0262	43	0.077	9.025	0.210	1812	2075	-263	-26529	-10.47	8017	8175	-159	-40247	-2.79
0.0255	44	0.106	9.131	0.208	2216	2367	-151	-26680	-10.53	18029	18307	-279	-40525	-2.81
0.0242	45	0.050	9.180	0.204	1298	1279	19	-26661	-10.53	15681	15774	-92	-40618	-2.81
0.0227	46	0.084	9.264	0.201	2379	2307	72	-26589	-10.50	15224	15180	44	-40574	-2.81
0.0216	47	0.140	9.405	0.200	3423	3613	-190	-26779	-10.57	8123	8224	-102	-40676	-2.82
0.0206	48	0.069	9.474	0.197	1691	1731	-40	-26819	-10.59	5801	5843	-42	-40717	-2.82
0.0198	49	0.353	9.827	0.201	1545	5883	-4338	-31157	-12.30	16954	24026	-7071	-47789	-3.31
0.0185	50	0.065	9.892	0.198	1753	1871	-118	-31276	-12.35	18143	18533	-390	-48179	-3.33

A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
Ranked by Model B		**Evaluated by Model C**												
Model B Probability that Vehicle Will Fail an ASM at the Decision Point	**Vehicle Ranking for Calling-In No-Sticker Targeting**	**Probability that Vehicle Will Fail an ASM at the Decision Point**	**Cumulative Sum of the Probabilities that Vehicle Will Fail an ASM at the Decision Point**	**Expected Fraction of Targeted Vehicles That Will Fail an ASM at the Decision Point**	**Expected FMD (miles/24months)**		**Expected ΔFMD (miles/24months)**	**Cumulative Expected ΔFMD (miles/24months)**	**Cumulative Expected %ΔFMD (% of sample total NIM FMD)**	**Expected FTP NX (g/24months)**		**Expected ΔFTP NX (g/24months)**	**Cumulative Expected ΔFTP NX (g/24months)**	**Cumulative Expected %ΔFTP NX (% of sample total NIM FTP NX)**
		If Vehicle is Called In		**If Vehicles in the Top Slice Are Called In**	**If Vehicle Is Called In**	**If Vehicle Remains in the Normal IM Process**	**If Vehicle Is Called In Rather Than Remaining in the Normal IM Process**	**If Vehicles In Top Slice Are Called In**	**If Vehicles In Top Slice Are Called In**	**If Vehicle Is Called In**	**If Vehicle Remains in the Normal IM Process**	**If Vehicle Is Called In Rather Than Remaining in the Normal IM Process**	**If Vehicles In Top Slice Are Called In**	**If Vehicles In Top Slice Are Called In**
0.0180	51	0.051	9.943	0.195	1168	1242	-73	-31349	-12.38	7900	8018	-118	-48296	-3.34
0.0175	52	0.140	10.083	0.194	3355	3600	-245	-31594	-12.47	17476	17683	-207	-48503	-3.36
0.0174	53	0.064	10.147	0.191	1468	1708	-240	-31834	-12.57	12705	13360	-655	-49158	-3.40
0.0169	54	0.107	10.254	0.190	2397	2674	-276	-32110	-12.68	6090	6319	-230	-49387	-3.42
0.0160	55	0.066	10.320	0.188	1758	1876	-117	-32228	-12.72	7403	7572	-169	-49556	-3.43
0.0152	56	0.128	10.448	0.187	3714	4151	-436	-32664	-12.89	11249	11632	-384	-49940	-3.46
0.0145	57	0.047	10.495	0.184	1013	1073	-60	-32724	-12.92	9136	9255	-119	-50059	-3.47
0.0139	58	0.041	10.536	0.182	1253	1263	-9	-32733	-12.92	8040	8253	-213	-50272	-3.48
0.0129	59	0.043	10.579	0.179	1221	1282	-61	-32794	-12.95	7382	7516	-134	-50407	-3.49
0.0122	60	0.061	10.641	0.177	1420	1477	-57	-32852	-12.97	12696	12809	-113	-50520	-3.50
0.0115	61	0.031	10.671	0.175	1029	1072	-43	-32895	-12.99	5047	5140	-94	-50614	-3.50
0.0111	62	0.030	10.702	0.173	733	897	-164	-33059	-13.05	14723	15695	-972	-51586	-3.57
0.0099	63	0.035	10.736	0.170	1120	1169	-49	-33108	-13.07	5835	5925	-90	-51675	-3.58
0.0093	64	0.033	10.769	0.168	764	864	-100	-33208	-13.11	6220	6326	-106	-51782	-3.58
0.0091	65	0.087	10.856	0.167	2162	2680	-518	-33726	-13.31	10133	10482	-349	-52131	-3.61
0.0086	66	0.029	10.885	0.165	833	818	15	-33711	-13.31	9843	10270	-427	-52558	-3.64
0.0082	67	0.034	10.919	0.163	1519	1495	24	-33687	-13.30	6037	6120	-82	-52640	-3.64
0.0072	68	0.014	10.933	0.161	397	397	0	-33687	-13.30	7839	7918	-79	-52719	-3.65
0.0069	69	0.033	10.966	0.159	895	916	-21	-33707	-13.31	7686	7737	-51	-52770	-3.65
0.0063	70	0.016	10.982	0.157	566	604	-38	-33745	-13.32	5041	5139	-98	-52868	-3.66
0.0061	71	0.015	10.997	0.155	597	620	-23	-33769	-13.33	4034	4080	-46	-52914	-3.66
0.0058	72	0.044	11.041	0.153	1229	1274	-45	-33814	-13.35	5108	5149	-42	-52956	-3.67
0.0054	73	0.018	11.059	0.151	437	479	-42	-33856	-13.37	20813	21119	-306	-53262	-3.69
0.0052	74	0.007	11.067	0.150	250	282	-32	-33888	-13.38	9222	9465	-243	-53505	-3.70
0.0050	75	0.015	11.081	0.148	384	454	-70	-33958	-13.41	11650	12078	-428	-53933	-3.73
0.0048	76	0.018	11.099	0.146	533	525	7	-33951	-13.40	6050	6020	29	-53904	-3.73
0.0044	77	0.022	11.121	0.144	726	737	-11	-33961	-13.41	8636	8652	-17	-53921	-3.73
0.0040	78	0.025	11.146	0.143	762	842	-79	-34040	-13.44	5735	5727	9	-53912	-3.73
0.0038	79	0.018	11.163	0.141	393	424	-32	-34072	-13.45	10602	10755	-153	-54066	-3.74
0.0035	80	0.023	11.186	0.140	619	665	-45	-34117	-13.47	4655	4723	-68	-54134	-3.75
0.0032	81	0.009	11.195	0.138	264	315	-52	-34169	-13.49	8578	9014	-436	-54570	-3.78
0.0031	82	0.017	11.212	0.137	524	552	-28	-34197	-13.50	6449	6571	-122	-54692	-3.79
0.0029	83	0.014	11.226	0.135	422	480	-58	-34254	-13.52	7061	7238	-177	-54869	-3.80
0.0026	84	0.005	11.230	0.134	88	97	-9	-34263	-13.53	6178	6168	10	-54859	-3.80
0.0023	85	0.026	11.256	0.132	812	863	-51	-34314	-13.55	6630	6702	-73	-54932	-3.80
0.0022	86	0.009	11.265	0.131	264	276	-12	-34326	-13.55	2437	2462	-25	-54957	-3.80
0.0020	87	0.007	11.272	0.130	153	191	-38	-34364	-13.57	7053	7243	-190	-55147	-3.82
0.0019	88	0.007	11.279	0.128	196	203	-7	-34371	-13.57	3726	3778	-52	-55199	-3.82
0.0017	89	0.028	11.307	0.127	759	948	-189	-34560	-13.64	5422	5612	-190	-55388	-3.83
0.0016	90	0.004	11.311	0.126	101	123	-22	-34582	-13.65	12600	12951	-351	-55740	-3.86
0.0014	91	0.006	11.317	0.124	198	223	-26	-34608	-13.66	6744	6885	-141	-55881	-3.87
0.0013	92	0.004	11.321	0.123	144	153	-9	-34617	-13.67	2721	2750	-30	-55910	-3.87
0.0012	93	0.003	11.324	0.122	84	94	-10	-34627	-13.67	10642	10739	-97	-56008	-3.88
0.0010	94	0.002	11.326	0.120	70	72	-3	-34630	-13.67	3621	3664	-43	-56050	-3.88
0.0008	95	0.002	11.328	0.119	83	88	-4	-34634	-13.67	3488	3509	-21	-56071	-3.88
0.0007	96	0.001	11.329	0.118	57	51	6	-34628	-13.67	3750	3750	0	-56071	-3.88
0.0005	97	0.001	11.330	0.117	25	26	-1	-34629	-13.67	6914	6912	2	-56069	-3.88
0.0003	98	0.003	11.333	0.116	58	58	0	-34629	-13.67	7558	7558	0	-56069	-3.88
0.0002	99	0.001	11.334	0.114	11	16	-5	-34634	-13.67	5270	5373	-103	-56172	-3.89
0.0000	100	0.000	11.334	0.113	0	0	0	-34634	-13.67	3399	3402	-3	-56175	-3.89
Total						253309					1444698			

The expected fraction of targeted vehicles that will fail an ASM at the decision point is given by Column E. Column E is calculated by summing all of the probabilities for the vehicles in a top slice and dividing by the number of vehicles in the slice. For example, for a slice of the top 3% of the vehicles, which is the top three vehicles, the expected fraction of vehicles that would fail the ASM at the decision point is the average of 0.306, 0.522, and 0.319, which equals 0.382. Because the failure probabilities tend to decrease for vehicles farther down into the list, the tendency is for the fraction of targeted vehicles that will fail an ASM at the decision point to decrease with larger fleet targeting percentages. This trend is shown by the plot in Figure 5-1 which is simply a plot of the values in Column E against Column B. The plot shows a general downward trend. Parts of the curve are monotonically decreasing; however, there are several instances when the expected fraction failing increases. This is caused by an unexpectedly large Model C failure probability such as that for Vehicle 18. Nevertheless, Figure 5-1 is an estimate of the fraction of vehicles that would fail a decision point ASM test for different fleet targeting percentages.

Figure 5-1. Fraction of Targeted Vehicles Expected to Fail an ASM at the Decision Point for the 100-Vehicle Example



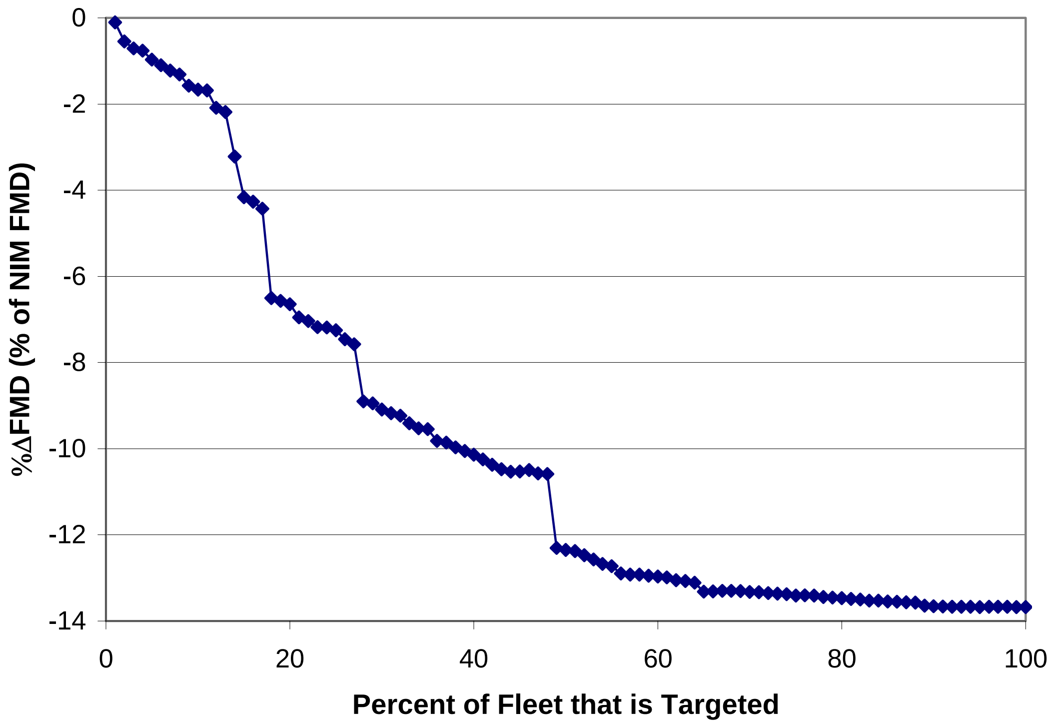
Columns F through J show the calculations for evaluation of the change in failed miles driven (ΔFMD). Column F gives the Model C estimates of the expected failed miles driven if each of the 100 individual vehicles were called-in, tested, and repaired if they failed. Column G gives the same calculation for the situation if the vehicle would remain in the Normal I/M Process. The difference between the two columns is shown in Column H, which gives the expected ΔFMD for each vehicle if the vehicle is called-in rather than remaining in the Normal I/M Process.

Ideally, the ranking of the 100 vehicles would be best for ΔFMD if the expected ΔFMDs were the smallest (that is, the largest negative values) at the top of the list. Scanning down the values in Column H shows that this is in general true; however, there are numerous large exceptions to the trend. For example, Vehicles 18 and 49 have quite large negative values and Vehicle 11 has a relatively small value. Clearly, these vehicles are examples of some level of inadequacy of the ranking method based on the Column A decision point failure probabilities calculated by Model B.

To get the %ΔFMD for different fleet targeting percentages, the calculations in Columns I and J are used. Column I is a cumulative sum of the Column H individual vehicle ΔFMDs for different slices starting at the top of the list. For example, for the top 3%, which are the top three vehicles, the cumulative expected ΔFMD is -1799 which is the sum of -257, -1127, and -415. Column J then expresses these cumulative expected ΔFMDs in terms of the percent of the 100 vehicle sample total FMD for the Normal I/M Process. This total is given at the bottom of Column G; if all 100 vehicles remained in the Normal I/M Process, they would be expected to drive 253,309 miles in a failed status over the 24 months after each vehicle's decision point. The values in Column J are calculated by dividing the values in Column I by this total Normal I/M Process failed miles driven value.

Inspection of the %ΔFMD values in Column J show that they are monotonically decreasing. The values in Column J are plotted against the fleet targeting percentages in Column B in Figure 5-2. The figure shows that if all of the 100 vehicles were called-in and not given a new certification sticker at the time but were required to follow their normal inspection schedule in spite of the call-in test and repair (that is, Call-In No-Sticker), the change in the failed miles driven would be a decrease of 13.67% with respect to the failed miles driven if none of the vehicles were called in. The figure also shows that, if approximately the top 20% of the targeted vehicles were called in, the ΔFMD would drop about 7% which is approximately half of the drop that would be achieved if all of the vehicles would be called in. This demonstrates the power of profiling: half of the achievable decrease in failed miles driven can be obtained by calling-in only 1/5 of the vehicles.

Figure 5-2. Change in Failed Miles Driven for the 100-Vehicle Example



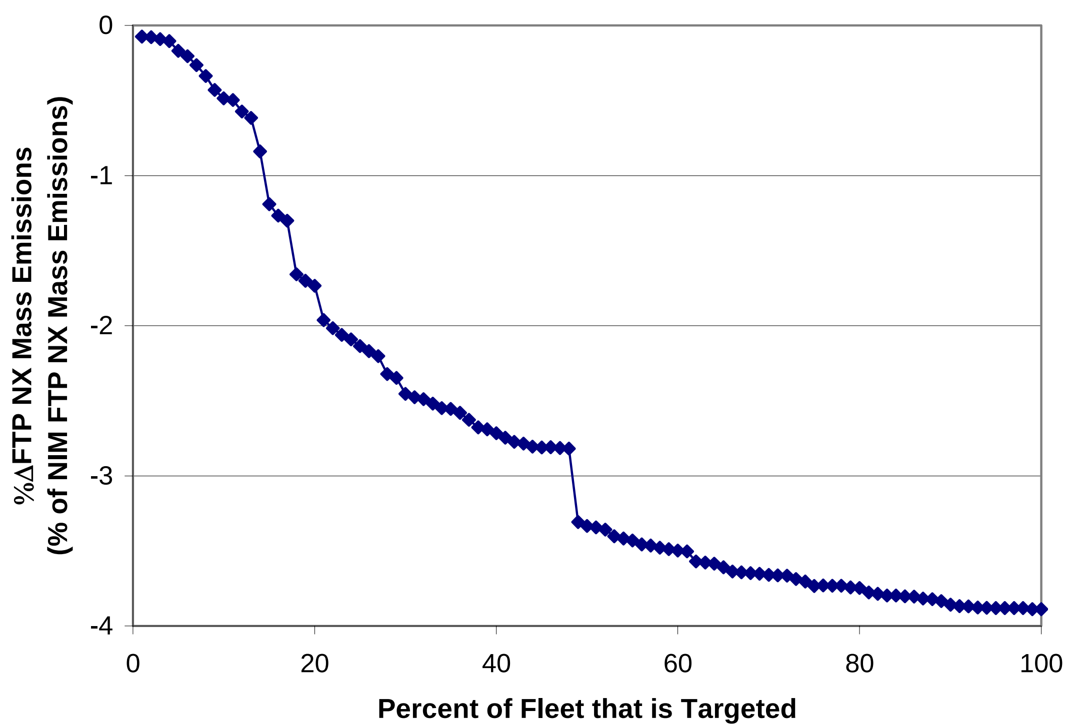
However, examination of Figure 5-2 also indicates that even better rankings of the 100 vehicles might be possible. The large abrupt drops in %ΔFMD by Vehicles 18, 28, and 49 demonstrate this. If these vehicles had been ranked higher in the list, then an even higher efficiency for Calling-In No-Sticker could have been achieved. It is possible that another ranking method could be better.

Columns K through O show the same sort of evaluation for ΔFTP NX. (In this example, we have chosen to examine only the FTP NX emissions. Evaluation of the ranking for the FTP HC and FTP CO mass emissions would be calculated analogously.) ΔFTP NX is calculated using Model C in Columns K, L, and M. Examination of the estimated ΔFTP NX values in Column N shows a generally decreasing trend in the individual ΔFTP NX values. The expected decreases in FTP NX for Calling-In No-Sticker are large for Vehicles 18 and 49 just as they were large for ΔFMD in Column H. However, the values of ΔFTP NX are not necessarily correlated well with the values of ΔFMD. For example, the value of ΔFTP NX for Vehicle 2 is -39 g/24 months, a quite low value, while the corresponding value for ΔFMD in Column H is -1127 miles/24 months which is a relatively high value. Differences of this sort can be a consequence of the different cutpoints that vehicles must meet. A repair of a specific vehicle might greatly reduce the failed miles driven, but because the vehicle has relatively low ASM cutpoints, the effect on the FTP mass emissions might be quite small.

The expected %ΔFTP NX mass emissions for different fleet percentages is provided by Column O and is calculated by dividing the cumulative expected ΔFTP NX emissions in Column N by the total expected FTP NX emissions if all vehicles remained in the Normal I/M Process (1,444,698 g/24 months), which is given at the bottom of Column L.

Figure 5-3 shows the %ΔFTP NX mass emissions for different fleet targeting percentages. The plot shows a decreasing trend with a drop of 3.89% in estimated FTP NX mass emissions if all of the vehicles would be called-in, tested, and repaired if necessary but still continue on their normal I/M schedule (that is, Call-In No-Sticker). This figure also shows, as did Figure 5-2, that if about 20% of the fleet is targeted, the estimated FTP NX mass emissions would be reduced by about half the amount that would be seen if all of the vehicles were called-in. It is unfortunate that Vehicle 49, which produced the large drop in ΔFTP NX mass emissions at 49% fleet targeting, was not ranked higher in the list.

Figure 5-3. Change in FTP NX Mass Emissions for the 100-Vehicle Example



The performance curves shown in Figures 5-1, 5-2, and 5-3 can be compared. The large decreases in %ΔFMD in Figure 5-2 produced by Vehicles 18, 28, and 49 produced only minor jogs in the failure probability at the decision point in Figure 5-1. In Figure 5-3, the effect of Vehicle 49 is the only major example where a vehicle appears to be out of order. The effects of Vehicles 18 and 28 that produced large drops in %ΔFMD in Figure 5-2 produced minor drops in %ΔFTP NX in Figure 5-3.

In addition to demonstrating how the calculations for evaluation are performed, we have seen that the three different quantities used for evaluation are different ways of looking at the vehicle rankings. Consequently, we can expect that different vehicle rankings may perform better for one evaluation quantity than for another. We can expect that there will be no one best way to rank the vehicles. The best rankings will depend on the quantities that are judged by ARB and BAR to be most important to improving I/M program performance.

5.4 Evaluation of Vehicle Rankings

Selection of Reference Model to Perform Evaluation – As mentioned earlier, because no vehicles received an I/M station ASM test or FTP emissions test at the decision point and at each of the 24 months after the decision point, there are no measured quantities in this study that can be used to directly evaluate vehicle ranking performance. Accordingly, Model D will be used to estimate the evaluation criteria for each vehicle ranking. For each intervention strategy, five plots will represent evaluation results using Model D to calculate the evaluation criteria. Those figures show the performance curves for different vehicle rankings with the assumption that Model D accurately mimics vehicle failure probabilities and FTP mass emissions. Recall that Model D is based on an analysis of VID history data and RSD data. An alternative is to use Model C, which is based on an analysis of just VID data, to calculate the evaluation criteria. Performance curves assuming that Model C accurately mimics the ASM failure probabilities and FTP mass emissions of the vehicles in the dataset are provided in Appendix O for comparison with the Model D plots in this section.

Probably neither Model C nor Model D is an entirely accurate representation of vehicle ASM failure probabilities or FTP emissions behavior. However, we believe that it is likely that Model D is a better model than Model C because Model D includes all of the same exact functionalities for VID history variables as Model C and, in addition, it includes functionalities for RSD measurements. While not having actual ASM test results and FTP emissions measurements for the vehicles in the dataset is a weakness of the evaluation, we believe that the analysis of the vehicle rankings using Model D to calculate the evaluation criteria estimates the maximum incremental benefits of adding RSD measurements to the I/M program.

Evaluation Approach – Now that we have described the methods used to produce the 35 different vehicle rankings for Directing, Exempting, Calling-In No-Sticker, Calling-In Sticker, and Scrapping, in this subsection we will evaluate the performance of each of the rankings in terms of the three evaluation criteria: %ΔFMD, %ΔFTP (HC, CO, NX), and FprobDP. Each of the intervention strategies will be considered separately by examining performance curves for each of the applicable vehicle rankings in five figures. A comparison of the relative locations of the performance curves on each figure will provide insight into the relative performance of the different vehicle ranking methods.

Each of the non-Scrapping intervention strategies are discussed below and contain five performance plots. The first plot is a display of %ΔFMD versus the percent of the fleet that is targeted. The next three plots display %ΔFTP HC, CO, and NX mass emissions as a percent of the fleet that is targeted. For Directing, Calling-In No-Sticker, and Calling-In Sticker, the curves on the first four plots that are lower represent those vehicle ranking methods that are better. The fifth plot shows the fraction of vehicles that would fail (pass, in the case of Exempting) an ASM test given at the decision point. For these plots, the curves that are higher throughout the range of vehicle targeting represent vehicle ranking methods that are better.

For the Scrapping strategy, five performance plots for the same evaluation criteria are shown. However, since we have found that the value of the candidate scrappage vehicle is critical to efficiently ranking scrappage vehicles, we show additional plots to gauge the relative performance of different ranking methods at constant market value of the targeted vehicles.

On each of the non-Scrapping performance plots, we consider the eleven ranking methods from Table 4-8 that apply to the strategy. Of the eleven, two rankings are based on change in failed miles driven (ΔFMD), six rankings are based on failure probability at the Decision Point (FprobDP), and three rankings are based on the measured RSD emissions concentrations for HC, CO, and NX.

On each of the Scrapping performance plots, we consider the twenty-seven ranking methods from Table 4-8 that apply to Scrapping. Of the twenty-seven, nine rankings are based on change in FTP HC, CO, or NX per vehicle value dollar (ΔFTP/$), six rankings are based on failure probability at the Decision Point (FprobDP), six rankings are based on failure probability at the Decision Point per vehicle value dollar (FprobDP/$), three rankings are based on the measured RSD emissions concentrations for HC, CO, and NX, and three rankings are based on the measured RSD emissions concentrations for HC, CO, and NX per vehicle value dollar.

Evaluation of vehicle rankings for Directing – The size of the benefit of Directing is proportional to the difference in performance of the station from which and to which a vehicle is directed. Clearly, if there is no difference in station performance, directing a vehicle provides no benefit. In this report, for the purposes of estimating the base benefits for Directing, we have assumed that high-performing stations performed accurate inspections and we assumed that average-performing stations performed completely useless inspections with no repairs being made. We do not believe either of these assumptions is actually true, but making the assumptions provides the maximum calculated benefits of Directing. Then, in the implementation report, the base benefits that are calculated here will be adjusted to correct for the estimated difference in actual performance between the average- and high-performing stations. Accordingly, all of the benefits (ΔFMD and ΔFTP) calculated for Directing and shown in Figures 5-4 through 5-7 are based on the assumption that all average-performing stations pass every vehicle, and all high-performing stations perform perfect emissions inspections.

We begin by considering the vehicle rankings based on Directing ΔFMD benefits (DI ΔFMD by C and DI ΔFMD by D). The performance curves for these two rankings are shown as the dashed lines in all five figures for Directing. Figure 5-4 shows that the best vehicle performance is the DI ΔFMD by Model D ranking. While this result is the best performing curve partly because the ranking and the evaluation of the ranking are both produced by the same values, the shape of the curve is an estimate of the performance curve that might be the result if vehicles were ranked by their actual change in failed miles driven when directed. For example, at 20% fleet targeting, %ΔFMD equals -13.3%. This is 65% of the value if all of the vehicles were targeted (-20.3%).

The two rankings shown by the thick dashed lines are based on ΔFMD, which is also the same quantity that is being evaluated in Figure 5-4. So it is not surprising that they perform well.

On the other hand, the vehicle rankings shown as the solid lines are based on the one point in time Fprobs at the decision point (FprobDP). Vehicle rankings using FprobDP are not focusing on ranking vehicles properly for %ΔFMD. Nevertheless, in Figure 5-4 we consider how FprobDP rankings perform from a %ΔFMD perspective. FprobDP rankings do not take into account vehicle usage, time until next inspections, previous-cycle initial-test result, or time since previous cycle. So, they are not as good as ranking vehicles by DI ΔFMD, which does take those features into account. When we consider FprobDP performance curves, we can think of them in terms of three groups.

Figure 5-4. Change in Failed Miles Driven Over 24 Months vs. Percent Fleet Targeting for Directing (Truth ≈ Model D)

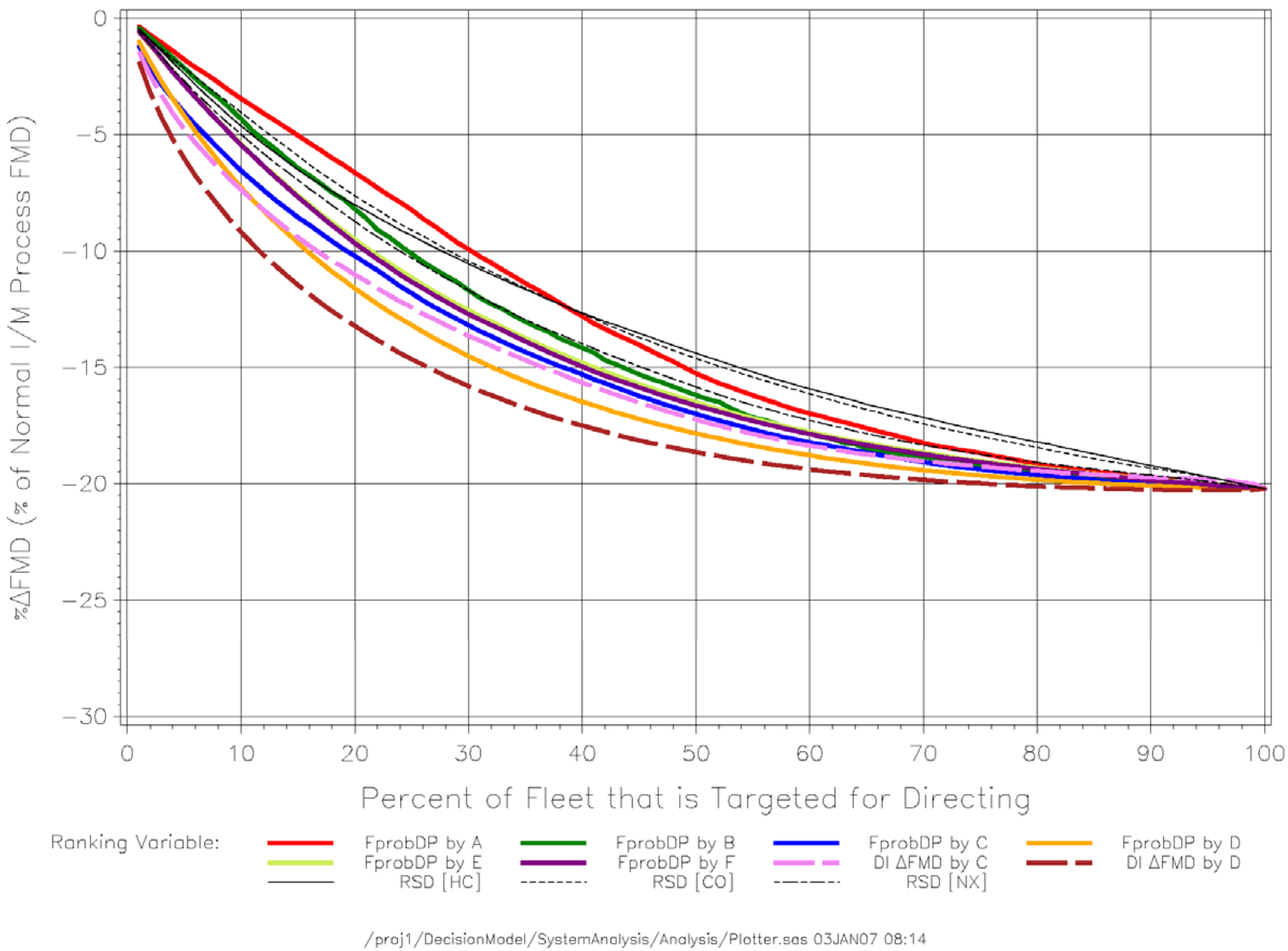


Figure 5-5. Change in FTP HC Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Directing (Truth ≈ Model D)

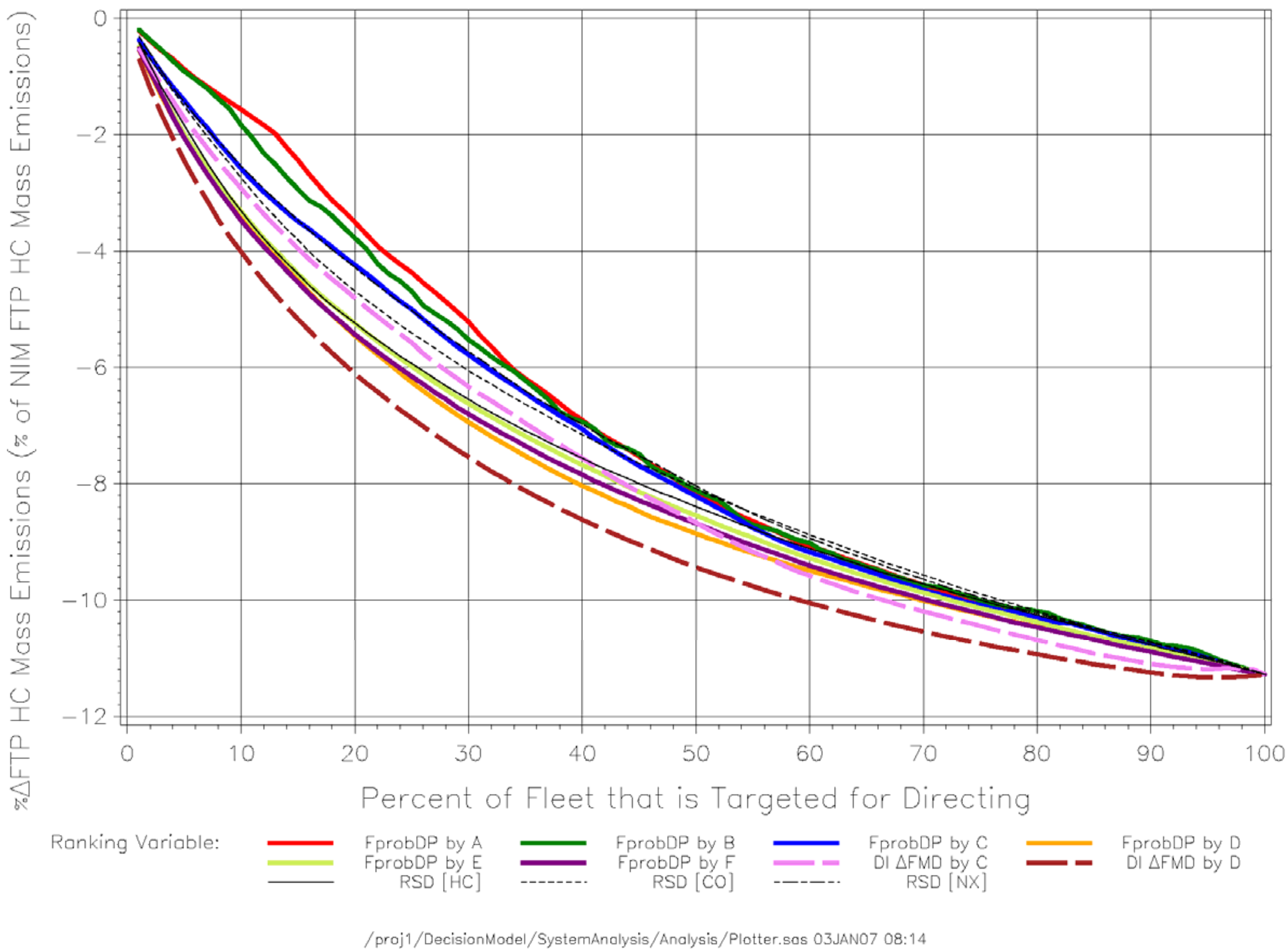


Figure 5-6. Change in FTP CO Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Directing (Truth ≈ Model D)

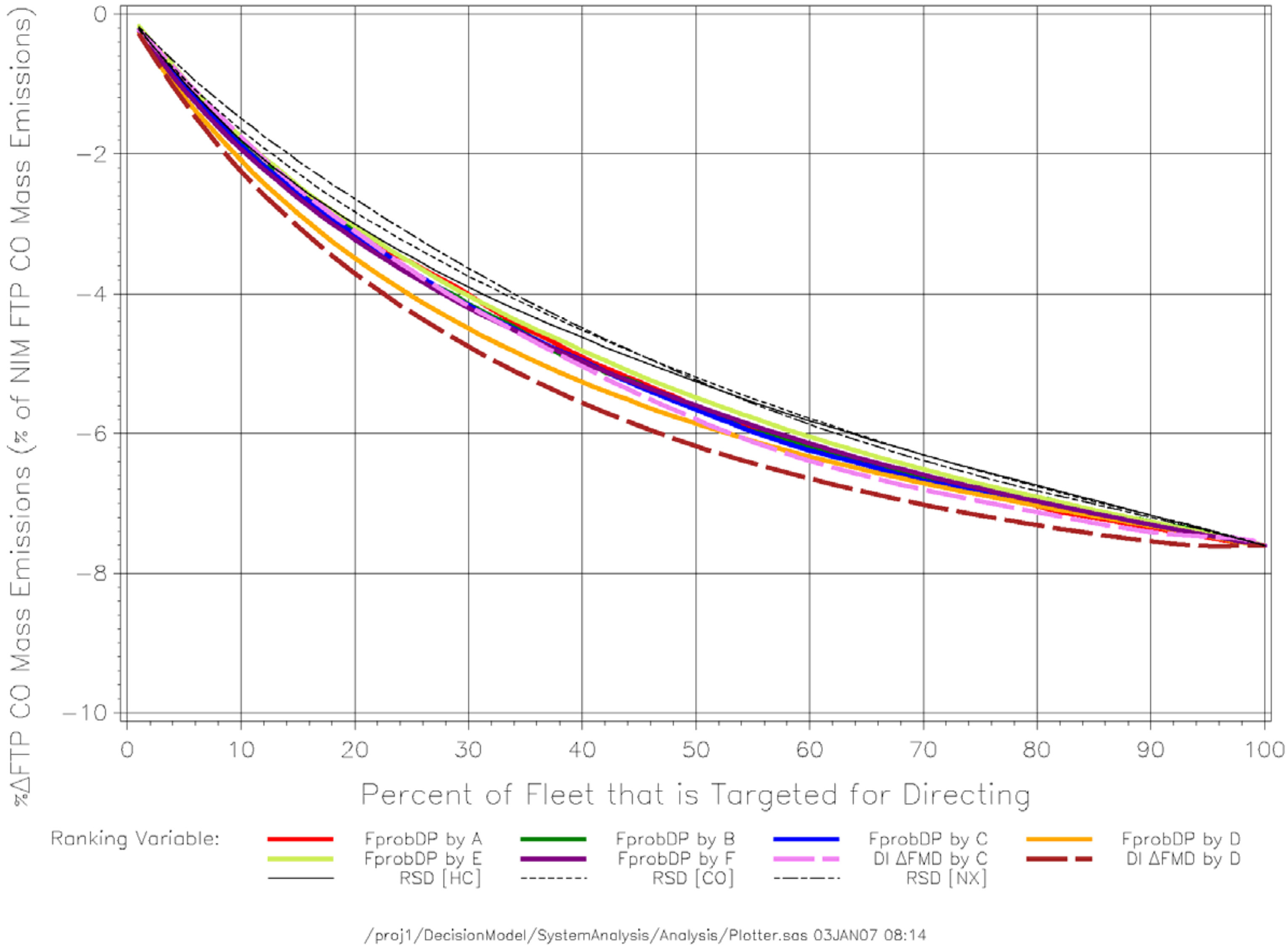


Figure 5-7. Change in FTP NX Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Directing (Truth ≈ Model D)

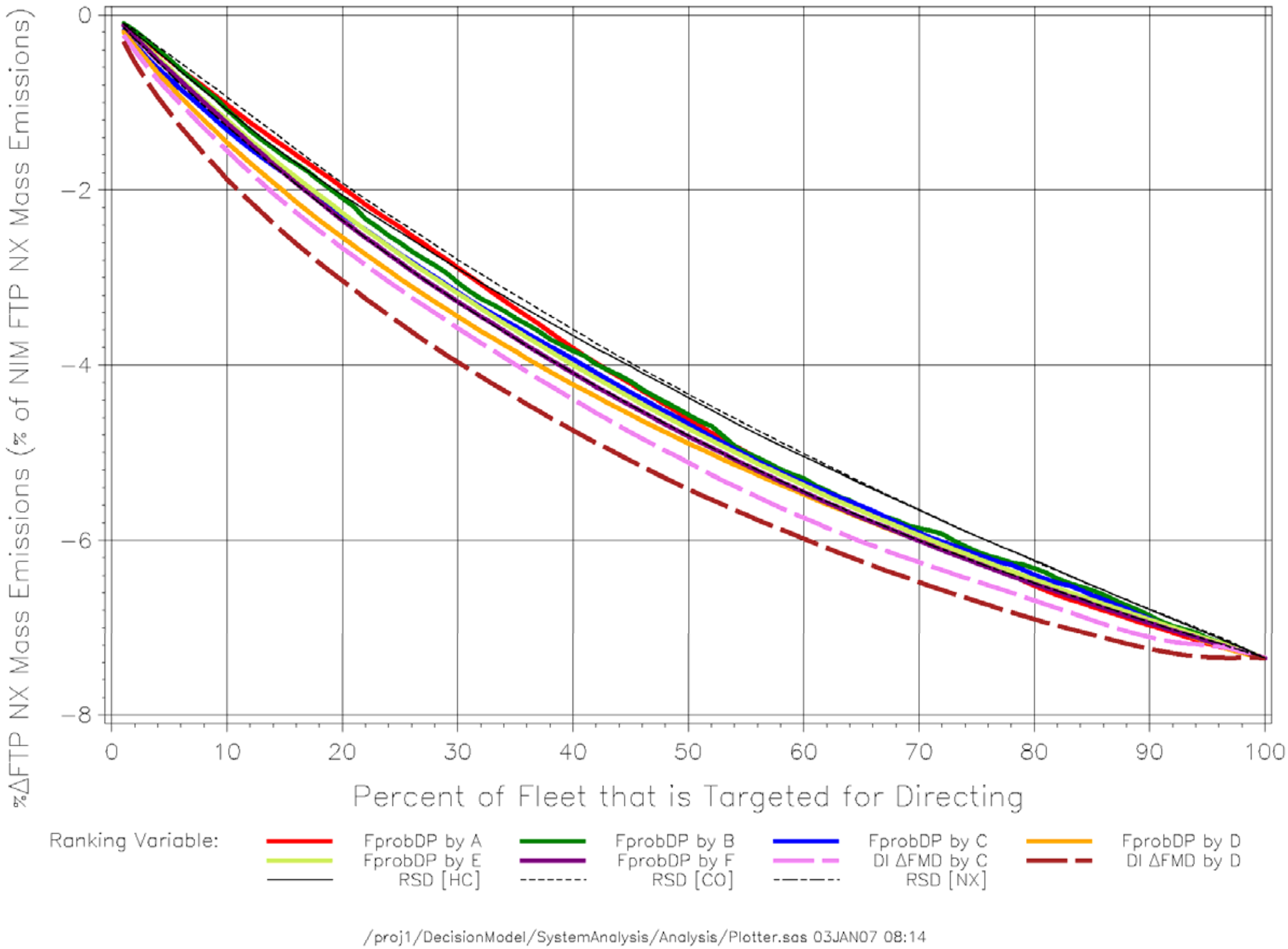
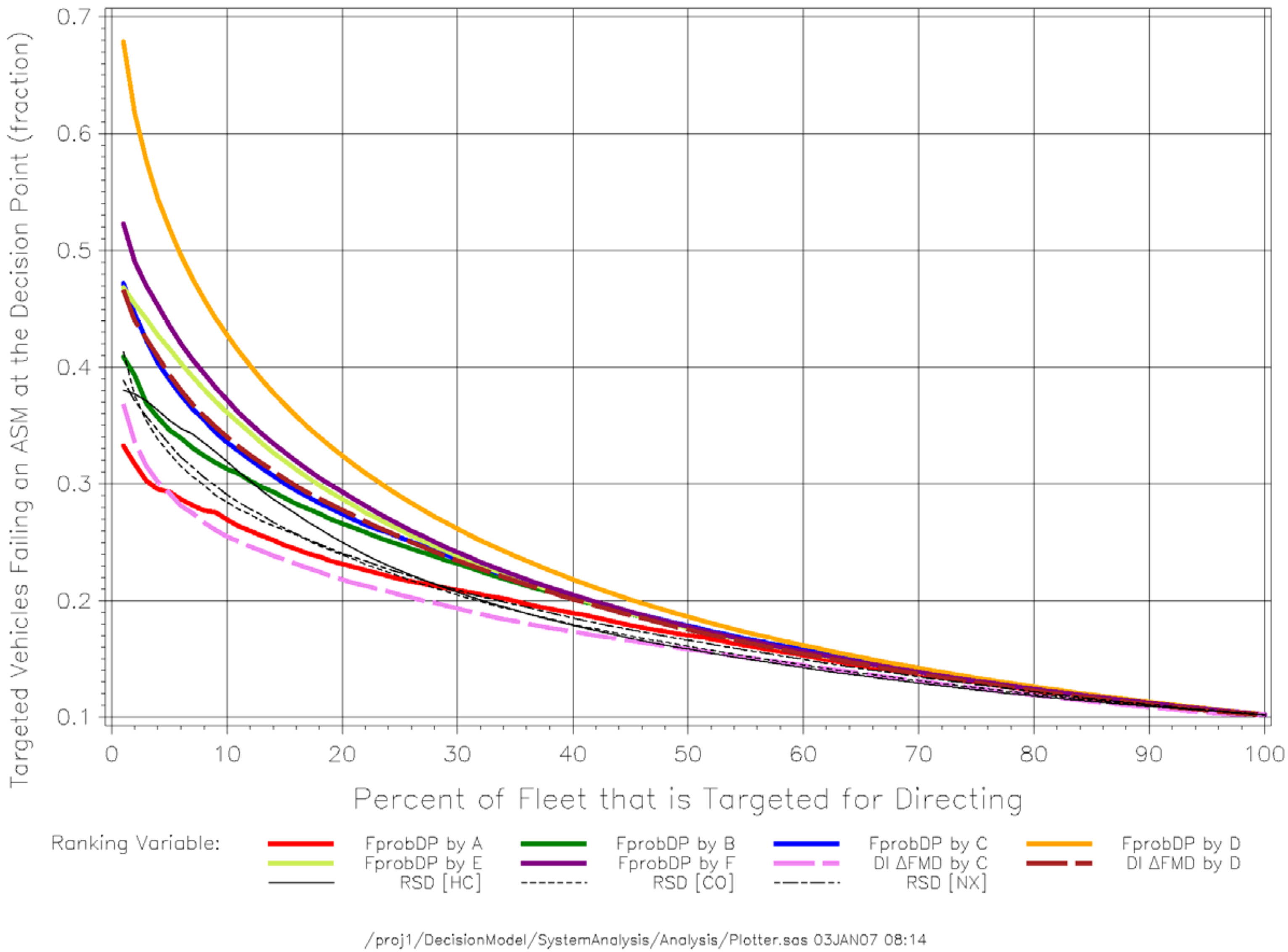


Figure 5-8. Fail Fraction of Targeted Vehicles at the Decision Point vs. Percent Fleet Targeting for Directing (Truth ≈ Model D)



The first group is FprobDP by A (red) and FprobDP by B (dark green). The FprobDP by A (red) curve tends to be the lower performing of the two. FprobDP by A is based on model year alone and FprobDP by B is similar to the recent HEP model.

The second pair of solid curves are those for FprobDP by C (blue) and FprobDP by D (orange). These two curves are considered in a pair because their ranking methods use FprobDP and have VID history inputs in common. The difference between them is that, in addition, FprobDP by D (orange) uses RSD inputs. Accordingly, the degree to which the orange curve is below the blue curve is a measure of the benefit to Directing of adding RSD information to VID history information.[37]

The third set of curves is for FprobDP by E (light green) and FprobDP by F (purple). FprobDP by E uses RSD information and ASM cutpoints while FprobDP by F uses only RSD information. For almost all plots in the study, the curves for these two FprobDPs tend to be very close to each other.

The performance curves for rankings based on RSD concentrations are shown as thin black solid and dashed lines. Figure 5-4 shows that simple rankings by RSD concentrations are inferior to several other ranking methods when considering the ΔFMD benefit. For example, for ΔFMD, the individual RSD concentrations are better than FprobDP by A (red), which uses only model year, and about as good as FprobDP by Model B (green), which is based on only vehicle description. But the individual RSD concentrations do not perform as well as all of the other ranking methods. The performance of FprobDP by Model F (purple) is superior to the individual RSD concentrations. As we shall see throughout this evaluation, Model F will almost always have performance superior to the individual RSD measurements. As described earlier, Model F is a new way to combine the three individual RSD measurements without using (arbitrary) RSD cutpoints. Model F produces a single quantity that can be used to rank a vehicle's probability of failing the overall ASM test. This ability of Model F to rank vehicles based on RSD measurements, rather than simply pass or fail them, is a big advantage.

Figures 5-5, 5-6, and 5-7 show the estimated FTP HC, CO, and NX emissions effects for the vehicle rankings for Directing. It is important to recognize that for these figures, the vehicle rankings are based on ΔFMD or FprobDP; the vehicles are not ranked for emissions improvements. However, the rankings are evaluated for emissions improvements.

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[37] Note, however, that if the evaluation criterion is Model C (see Figure O-4), the relative positions of the blue and orange curves are switched.

The figures show that if all vehicles were directed (and average-performing stations were completely ineffective, but high-performing stations had the average performance of the stations in the I/M program), the %ΔFTP HC would change -11.2%; ΔFTP CO would change -7.6%; and ΔFTP NX would change -7.4% using Model D to calculate these evaluation criteria. These quantities represent estimates of the maximum emissions benefit that can be achieved by Directing.

The dashed lines in Figures 5-5 through 5-7 show the estimated FTP emissions performance curves for vehicle rankings by DI ΔFMD by Model C and DI ΔFMD by Model D when Model D is used to evaluate. Appendix O Figures O-5, O-6, and O-7 show the corresponding curves when Model C is used to evaluate ΔFTP performance. The important observation to take from these six figures is that the vehicle ranking DI ΔFMD by Model D always performs better than DI ΔFMD by Model C – even when the evaluation criteria are calculated using Model C. We shall see that this trend is also always true for Exempting, Calling-In No-Sticker, and Calling-In Sticker as well as for Directing. We believe that this result means that RSD information does have the ability to improve the emissions capture through targeting for Directing, Exempting, Calling-In No-Sticker, and Calling-In Sticker. The question then becomes, "Is this improved performance worth the cost of measuring RSD throughout the state?" That will be addressed in a subsequent report.

The ΔFMD rankings (thick dashed lines) in Figures 5-5 through 5-7 are the best or at least in the better half of the rankings for FTP emissions. However, there are some cases where FprobDP rankings are slightly better. Just as for ΔFMD in Figure 5-4, the relative order of the FprobDP curves in Figures 5-5 through 5-7 move around as the FTP emissions being evaluated change.

The RSD concentration rankings in Figures 5-5 through 5-7 are relatively poor performers at ranking vehicles for Directing. However, when the RSD measurements are combined using the FprobDP by F model (purple), the performance for Directing is noticeably improved.

Figure 5-8 shows the fraction of the targeted vehicles that are estimated to fail an ASM test at the decision point as evaluated by Model D. While FprobDP is not strictly a benefit, it is an evaluation quantity that might be called the embarrassment factor. We would want a large fraction of the vehicles that are Directed to fail the ASM test. Figure 5-8 shows that at 100% targeting between 10 and 11% of the vehicles would fail an ASM test at the decision point. As usual, the thick dashed lines in the figure show vehicle rankings based on ΔFMD. The fail fractions for the thick dashed lines are not as high as for some of the solid lines, which represent vehicle rankings based solely on FprobDPs. This is because the entire focus of the FprobDP rankings is to get the failed fraction at the decision point as high as they can. While the ΔFMD rankings do consider fail fraction at the decision point, they also consider other factors that are important to the general success of the I/M program and to the airshed.

In Figure O-8, where the evaluation criteria are calculated by Model C, the fail fraction curves for ΔFMD rankings by both Model C and Model D are very close to the same. However, in Figure 5-8 where the evaluation criteria are calculated by Model D, the ΔFMD ranking by Model D is substantially higher than the ranking produced by ΔFMD by Model C. Because of this asymmetry in the performance curves for fail fraction when vehicles are ranked for ΔFMD by Model C and Model D, we conclude that the vehicle ranking by ΔFMD by Model D will identify targeted sets of vehicles that have higher failure rates.

The figures where Model D was used to calculate the evaluation criteria can be used to estimate the maximum incremental improvement in the benefits produced by adding RSD information to the intervention strategy. A comparison of the benefit of the ΔFMD by D ranking over the ΔFMD by C ranking provides the improvement. For example, Figures 5-4 through 5-8 show that at 40% fleet targeting the %ΔFMD, %ΔFTP HC, %ΔFTP CO, %ΔFTP NX, and FprobDP are -15.7, -7.6, -5.0, -4.4, and 0.17 for vehicle ranking by DI ΔFMD by C and are -17.5, -8.6, -5.6, -4.8, and 0.20 for vehicle ranking by DI ΔFMD by D. These all represent small incremental improvements in benefits caused by adding RSD information to VID history information when Model D provides the evaluation criteria.[38]

Evaluation of vehicle rankings for Exempting – Ranking vehicles for Exempting uses the same basic raw modeling numbers as ranking vehicles for Directing. The reason for this is that in both cases, the ΔFMD benefits and ΔFTP benefits have the same magnitude but have the opposite sign. In the case of directing vehicles to high-performing stations, the result is a decrease in failed miles driven and a decrease in estimated FTP mass emissions because vehicles that would not necessarily receive a proper repair at an average-performing station get higher quality repairs at high-performing stations. In the case of Exempting, vehicles that are low risk with respect to failed miles driven in the 24 months after the decision point are targeted first. These vehicles, by definition, get an inspection certification without receiving an ASM test or

[38] Note that the corresponding Figures O-4 through O-8, where Model C provides the evaluation criteria, give different incremental improvements associated with adding RSD information. The changes associated with adding RSD sometimes even indicate a degradation of ΔFMD.

any repairs. Thus, exempting vehicles causes increases in failed miles driven and FTP emissions. The modeled benefits from both Directing and Exempting intervention activities are calculated as the difference between the NIM and DX paths for the 24 months after the decision point.

Because of this connection between the benefits of Directing and the benefits of Exempting, the performance curves for Exempting in Figures 5-9 through 5-12 for %ΔFMD and %ΔFTP evaluation criteria are the same as Figures 5-4 through 5-7 for Directing with the sign of the vertical axis switched. The result is that the relative performance of the different ranking variables for ΔFMD and ΔFTP for Exempting is the same as for Directing.

Figure 5-9 shows that vehicle rankings by EX ΔFMD by Model C and Model D allow significant fractions of the fleet to be targeted for Exempting. Keep in mind that the 69,629-observation dataset for which these curves were developed already had vehicles with the newest model years exempted from the I/M program. Even so, Figure 5-9 indicates that 30% of the remaining vehicles might be exempted if vehicles are ranked by either EX ΔFMD by C or by EX ΔFMD by D when considering the %ΔFMD. The %ΔFTP mass emissions effects for a 30% exemption are larger as shown in Figures 5-10 through 5-12.

Just as for Directing, ranking vehicles for Exempting using EX ΔFMD by D always had better FTP emissions performance than ranking vehicles by EX ΔFMD by C as seen in Figures 5-10 through 5-12 (and Figures O-10 through O-12 where Model C provides the evaluation criteria). Just as for Directing, we conclude that ranking vehicles by ΔFMD using Model D, which includes RSD information, is better than by Model C, which does not include RSD information. Thus, for exempting vehicles, having RSD information allows vehicles to be selected for Exempting while keeping the mass emissions released to the airshed from the exempted vehicles lower than if the RSD information were not available. The question of whether getting the RSD information for vehicles for exempting is cost-effective will be investigated in the subsequent implementation report.

The third evaluation criterion for Exempting is not similar to Directing. For Exempting, we would want to have a large fraction of the targeted vehicles pass an ASM test at the decision point. Of course, vehicles that are exempted would not actually receive an ASM test at the decision point, but because we can estimate the fraction passing at the decision point using Models C and D, we can view the estimated results as shown in Figure 5-13.

Figure 5-9. Change in Failed Miles Driven Over 24 Months vs. Percent Fleet Targeting for Exempting (Truth ≈ Model D)

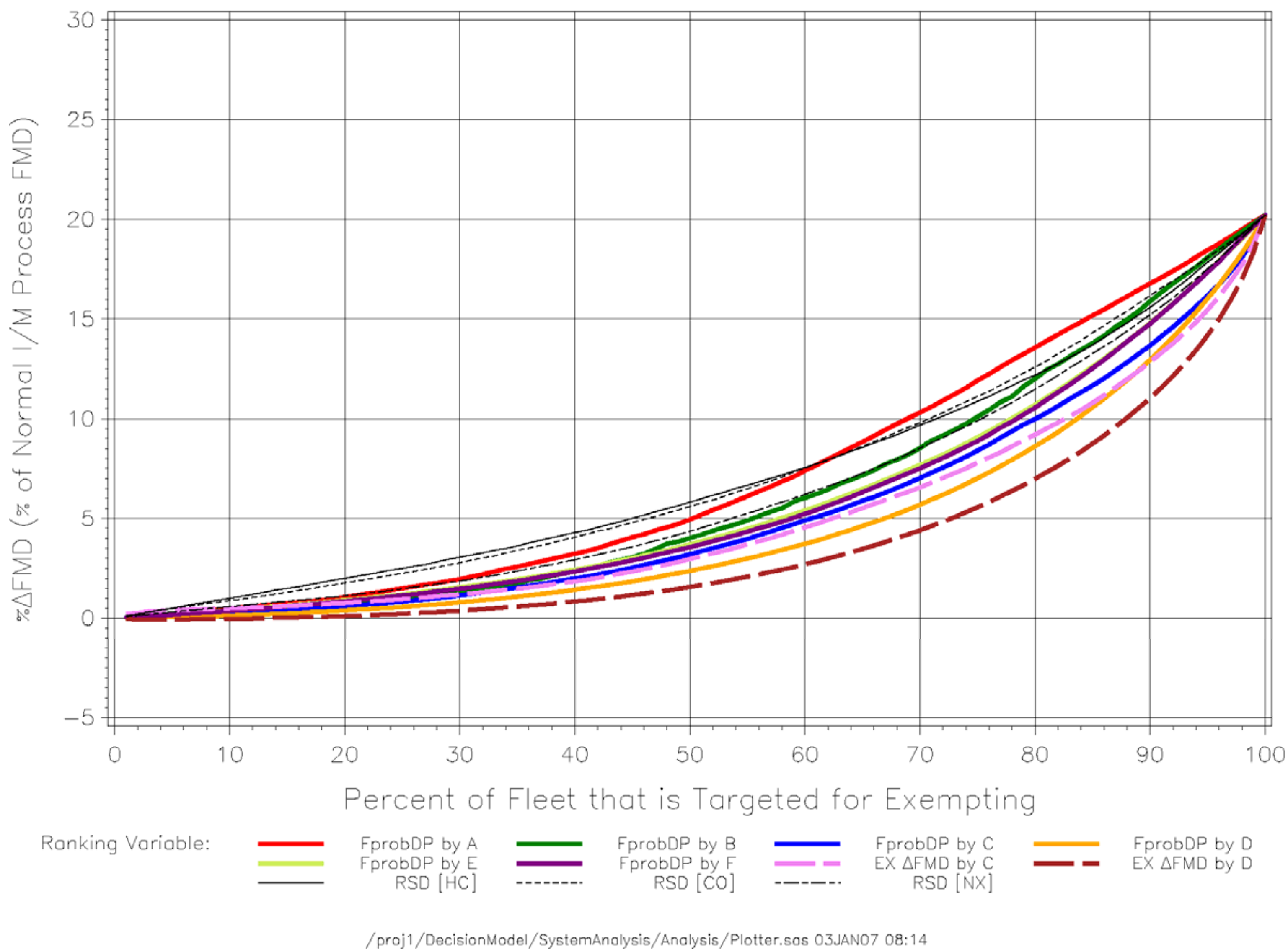


Figure 5-10. Change in FTP HC Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Exempting (Truth ≈ Model D)

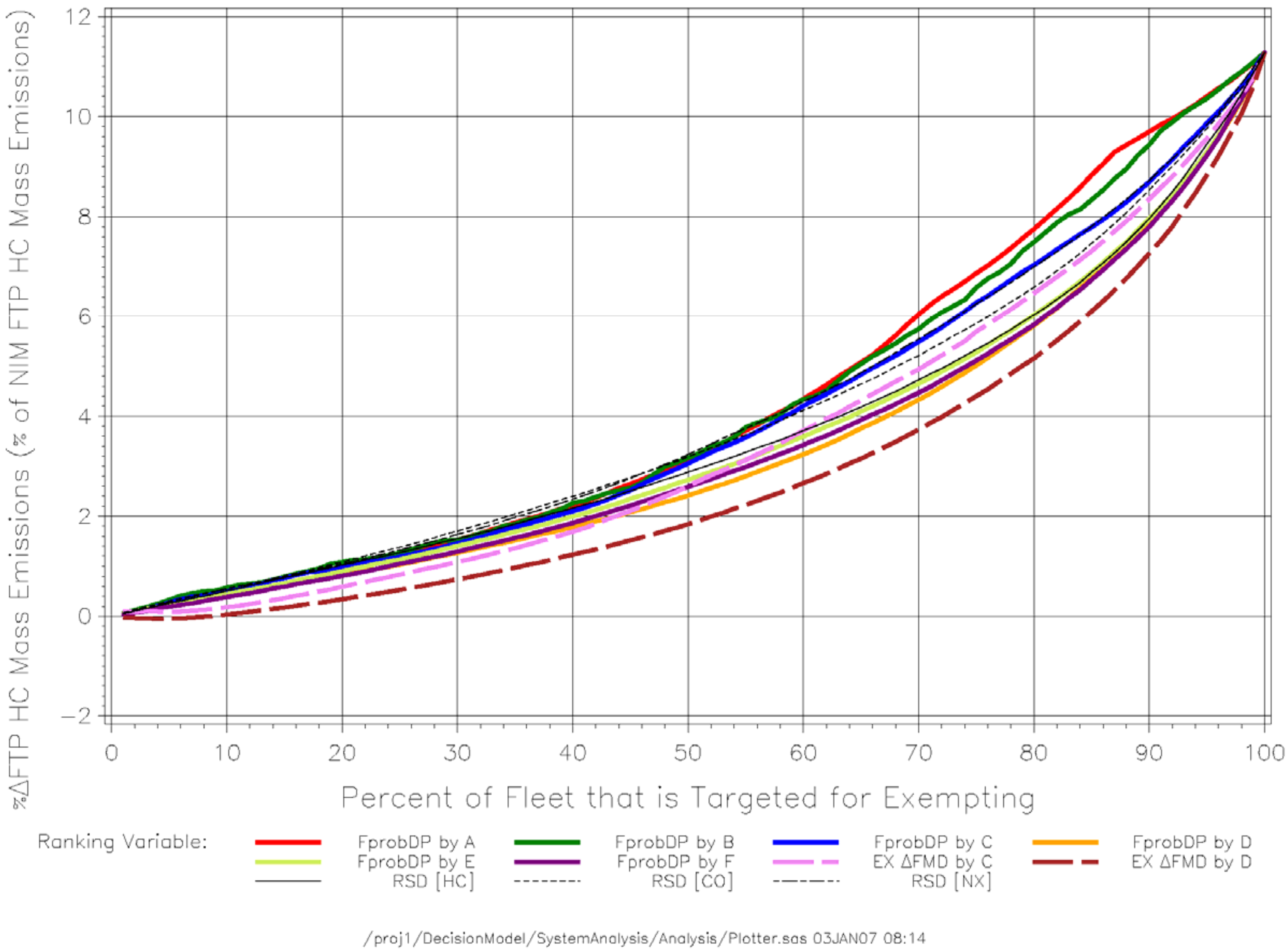


Figure 5-11. Change in FTP CO Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Exempting (Truth ≈ Model D)

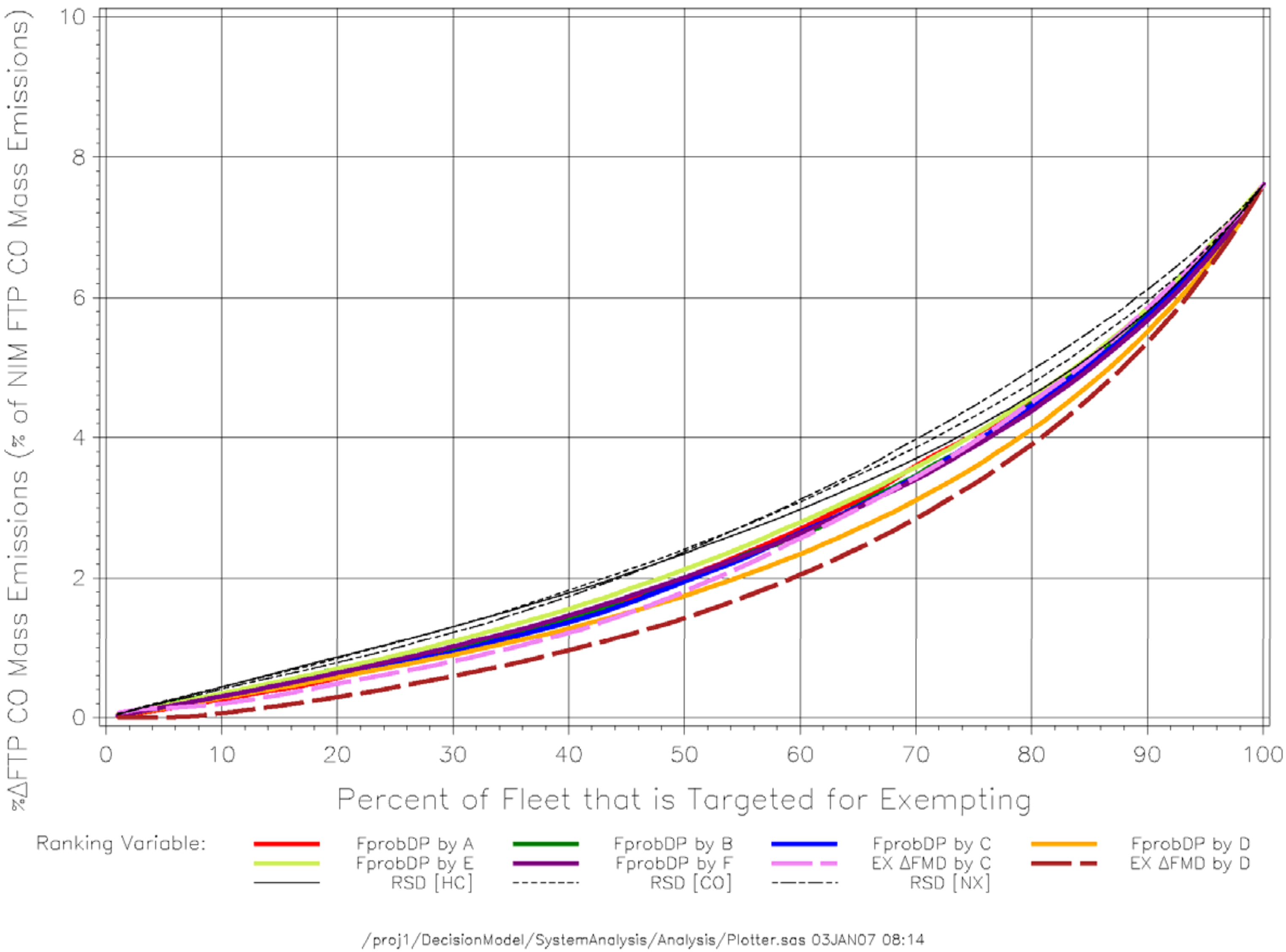


Figure 5-12. Change in FTP NX Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Exempting (Truth ≈ Model D)

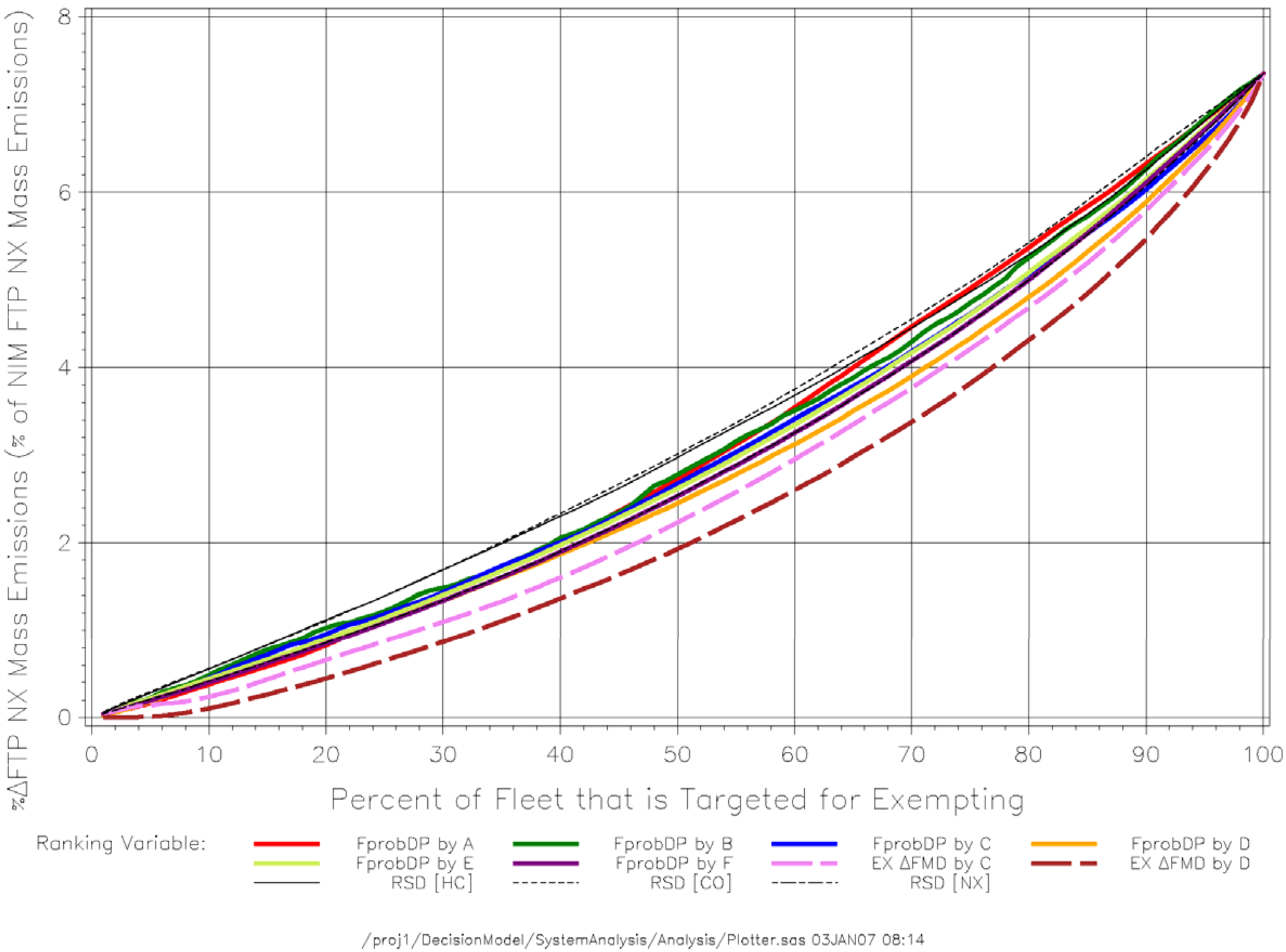
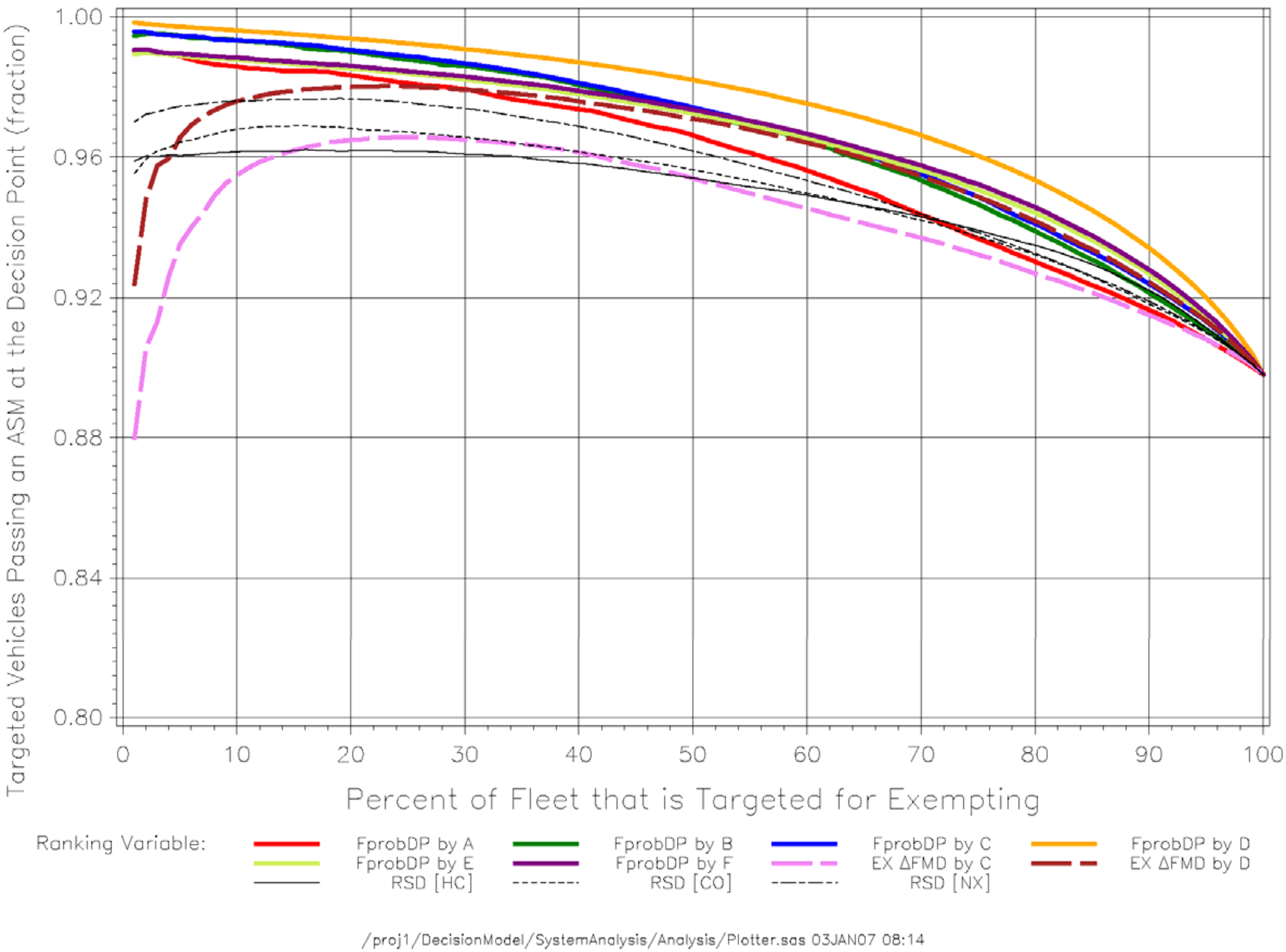


Figure 5-13. Pass Fraction of Targeted Vehicles at the Decision Point vs. Percent Fleet Targeting for Exempting (Truth ≈ Model D)



The thick dashed curves in Figure 5-13 show the percent of the vehicles that would pass an ASM at the decision point for vehicle rankings based on EX ΔFMD by C and by D. The figure shows that the vehicle ranking EX ΔFMD by D produces a larger fraction of vehicles that would pass a decision point ASM. This is still the case even if Model C is used to calculate the evaluation criterion as shown by Figure O-13. We believe that this result clearly shows that using RSD information in EX ΔFMD by D has better performance than if the RSD information is not present.

The solid lines in Figure 5-13 show the fraction of targeted vehicles that would pass an ASM test at the decision point for vehicle rankings based on FprobDP by the different models. These curves tend to perform better than the ΔFMD vehicle rankings and the RSD concentration rankings because the FprobDP rankings focus is solely on maximizing the evaluation criteria of fraction passing an ASM test at the decision point.

The figures where Model D was used to calculate the evaluation criteria can be used to estimate the maximum incremental improvement in the benefits produced by adding RSD information to the intervention strategy. A comparison of the benefit of the ΔFMD by D ranking over the ΔFMD by C ranking provides the improvement. For example, Figures 5-9 through 5-13 show that at 20% fleet targeting the %ΔFMD, %ΔFTP HC, %ΔFTP CO, %ΔFTP NX, and FprobDP are 0.8, 0.6, 0.5, 0.7, and 0.035 for vehicle ranking by EX ΔFMD by C and are 0.1, 0.3, 0.3, 0.4, and 0.020 for vehicle ranking by EX ΔFMD by D. These all represent small incremental improvements in performance caused by adding RSD information. Exempting always causes increases in failed miles driven, mass emissions, and fail rates; however, the analysis indicates that the size of the increases incurred during Exempting can be minimized to quite low levels if intelligent methods of vehicle selection are used.

Evaluation of vehicle rankings for Calling-In No-Sticker – The performance curves for Calling-In No-Sticker for %ΔFMD are shown in Figure 5-14. The figure shows that if all vehicles were called in and not given a sticker, the %ΔFMD based on Model D would be -8.4% of the total failed miles driven for the fleet under the Normal I/M Process. From Figure 5-14 the performance curve for CN ΔFMD by C indicates that for 20% fleet targeting the %ΔFMD is -5.6% which is 67% of the drop relative to the %ΔFMD if all vehicles were targeted. The corresponding value for CN ΔFMD by D is a 74% drop at 20% fleet targeting relative to the %ΔFMD at 100% fleet targeting.

Figure 5-14. Change in Failed Miles Driven Over 24 Months
vs. Percent Fleet Targeting for Calling-In No-Sticker (Truth ≈ Model D)

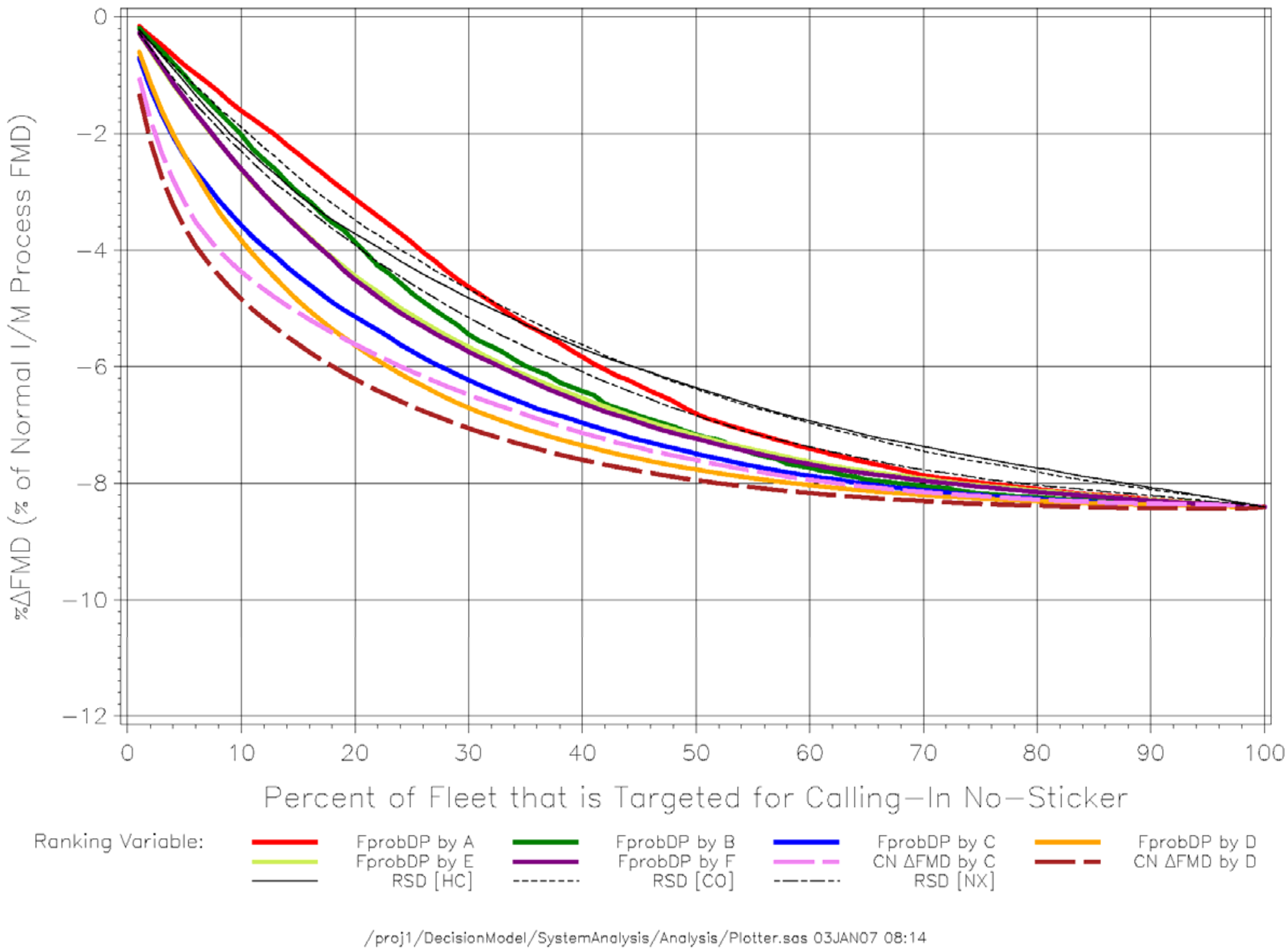


Figure 5-15. Change in FTP HC Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Calling-In No-Sticker (Truth ≈ Model D)

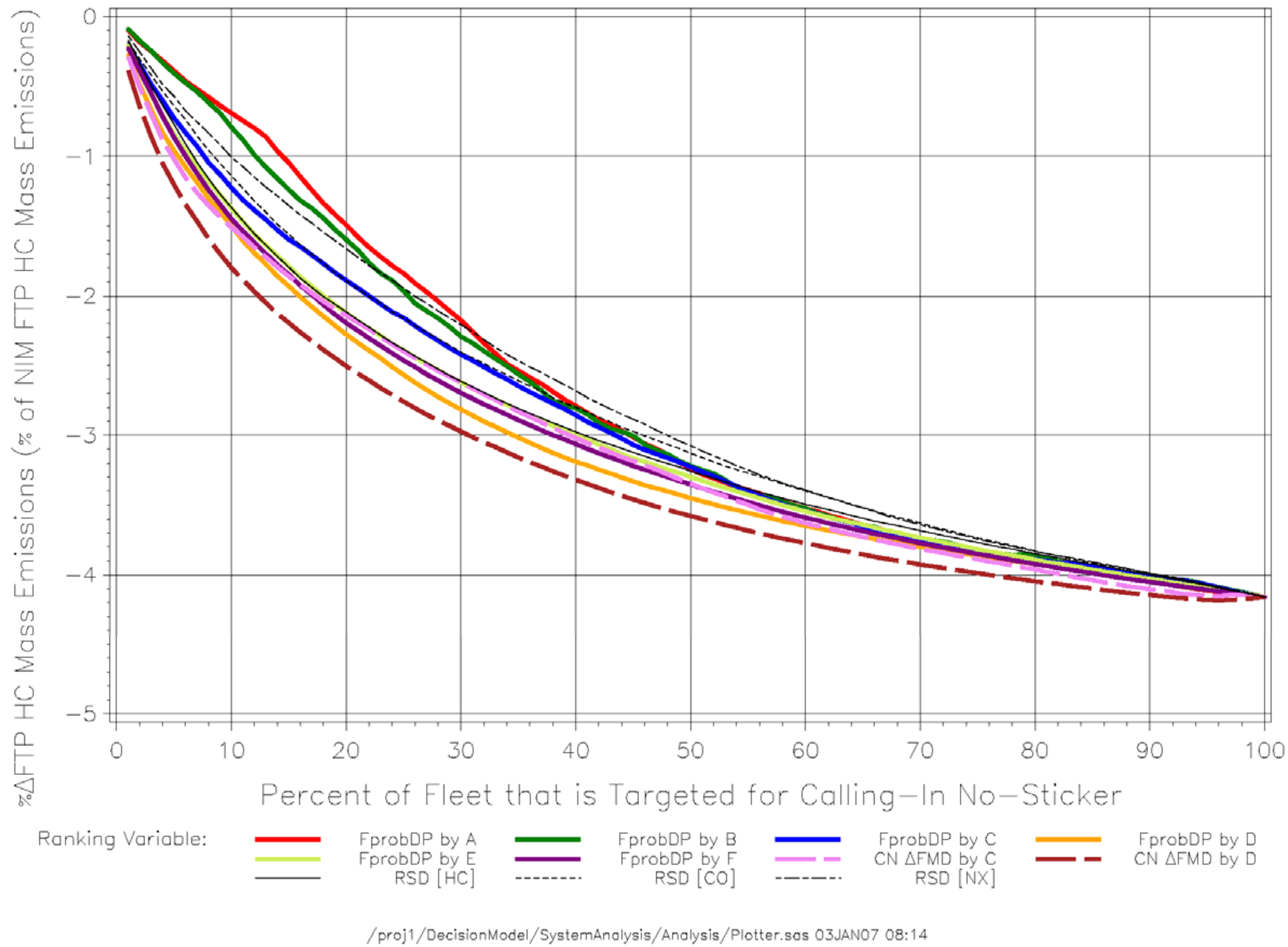


Figure 5-16. Change in FTP CO Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Calling-In No-Sticker (Truth ≈ Model D)

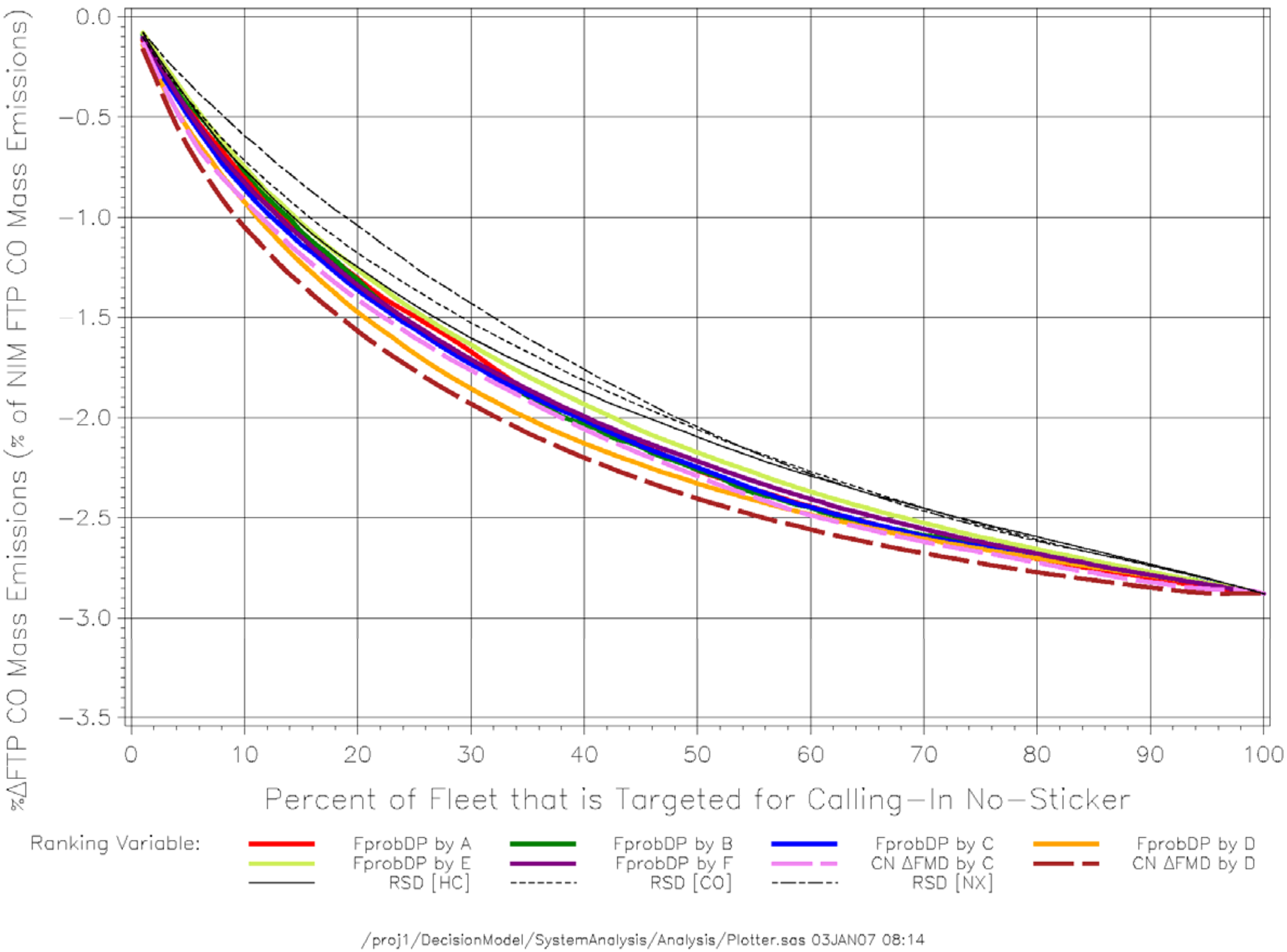


Figure 5-17. Change in FTP NX Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Calling-In No-Sticker (Truth ≈ Model D)

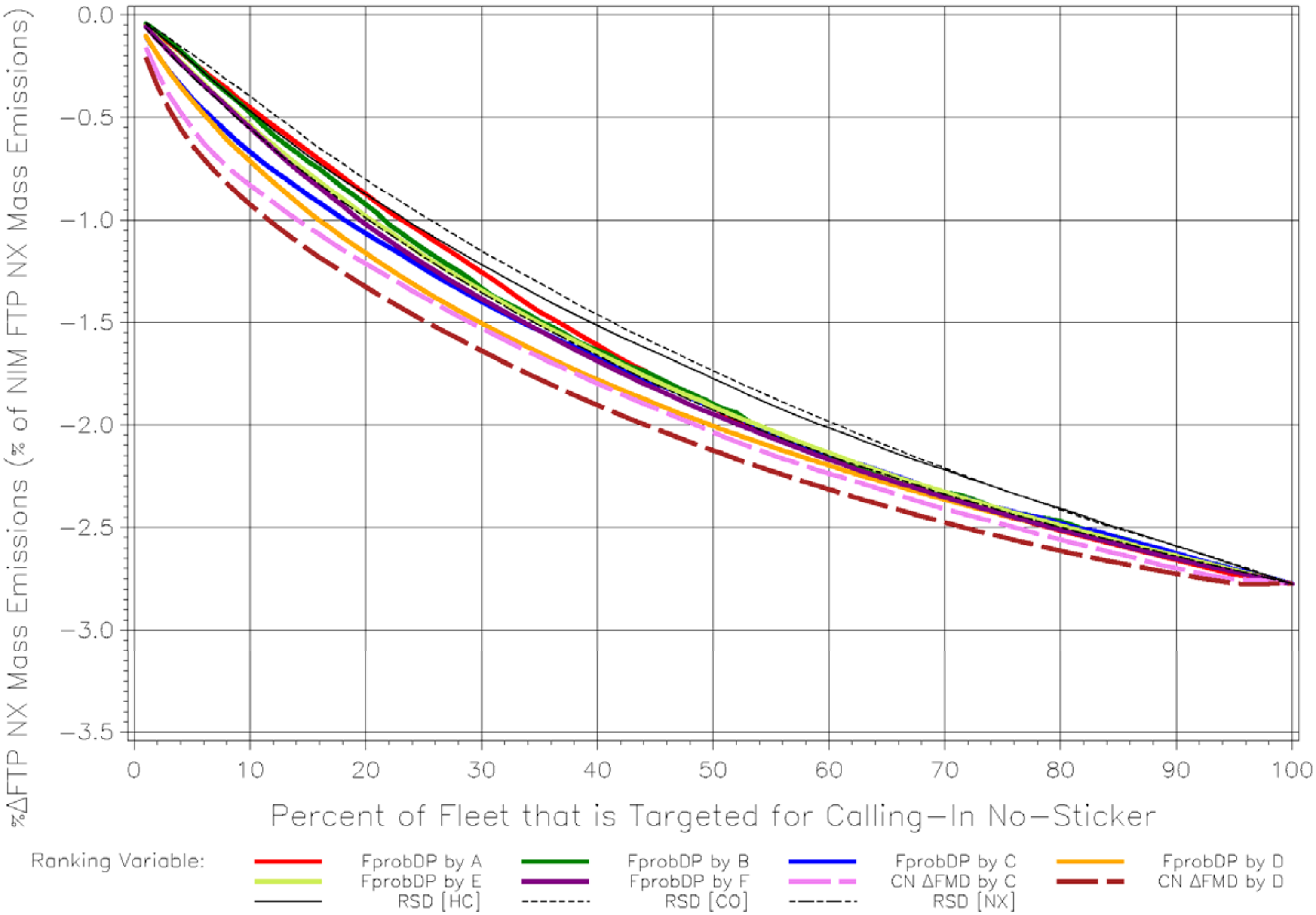


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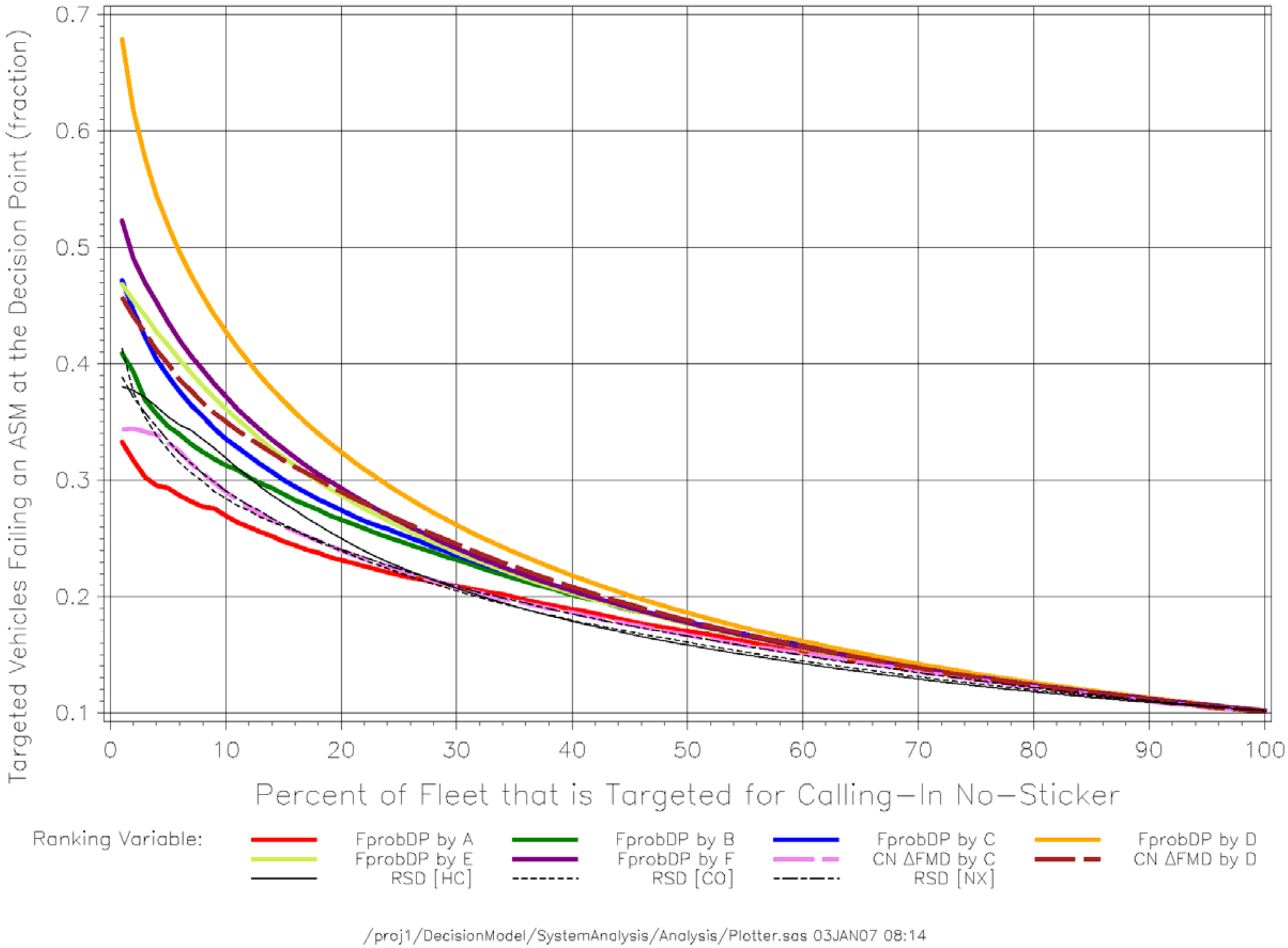
Figure 5-18. Fail Fraction of Targeted Vehicles at the Decision Point vs. Percent Fleet Targeting for Calling-In No-Sticker (Truth ≈ Model D)



The thick dashed curves in Figure 5-14 tend to indicate that vehicle targeting for Calling-In No-Sticker using ΔFMD by either Model C or Model D are superior to vehicle rankings that use FprobDPs or RSD concentrations.

Figures 5-15 through 5-17 show the performance curves for %ΔFTP HC, CO, and NX. Just as for Directing, the curves for CN ΔFMD by D (brown dashes) always have estimated FTP emissions performance equal to or superior to that of vehicle rankings by CN ΔFMD by C (light purple dashes). We believe that this indicates that vehicle rankings for Calling-In No-Sticker by ΔFMD by Model D is superior to that using Model C. The interpretation of the vehicle rankings for the FprobDPs, which are shown by the solid lines, is the same as for Directing since the relative locations of the curves are the same. If all of the vehicles were subjected to Calling-In No-Sticker, Figures 5-15 through 5-17 indicate that the %ΔFTP HC would change -4.2%; ΔFTP CO would change -2.9%; and the ΔFTP NX would change -2.8% using Model D to calculate these evaluation criteria. Note that these 100% targeting ΔFTP reduction values are substantially smaller than those calculated from Figures 5-5 through 5-7 for Directing. This does not necessarily mean that greater benefits can be achieved through Directing since the Directing curves do not take into account the level of inaccuracies at average-performing stations.

Figure 5-18 shows the fraction of vehicles that would be expected to fail an ASM at the decision point for the Calling-In No-Sticker intervention activity. Just as for Directing, when Model D is used to calculate the evaluation quantity, the vehicle ranking by CN ΔFMD by D (brown dashes) is superior to vehicle ranking by CN ΔFMD by C (light purple dashes). However, when the fail fraction is calculated using Model C as shown in Figure O-18, the dashed lines for ranking by CN ΔFMD by C and CN ΔFMD by D are nearly on top of each other. Again, this indicates to us that Model D, which includes RSD information in addition to VID history information, is better at targeting vehicles that will fail a call-in ASM at the decision point.

The solid lines in Figure 5-18 show the ability of the FprobDPs to rank vehicles for failing a call-in no-sticker ASM at the decision point, which is the sole purpose for which they were designed.

The figures where Model D was used to calculate the evaluation criteria can be used to estimate the maximum incremental improvement in the benefits produced by adding RSD information to the intervention strategy. A comparison of the benefit of the ΔFMD by D ranking over the ΔFMD by C ranking provides the improvement. For example, Figures 5-14 through 5-

18 show that at 5% fleet targeting the %ΔFMD, %ΔFTP HC, %ΔFTP CO, %ΔFTP NX, and FprobDP are -3.2, -1.0, -0.6, -0.6, and 0.33 for vehicle ranking by CN ΔFMD by C and are -3.6, -1.2, -0.7, -0.6, and 0.40 for vehicle ranking by CN ΔFMD by D. These all represent small incremental improvements in benefits caused by adding RSD information.

Evaluation of vehicle rankings for Calling-In Sticker – The performance for Calling-In Sticker are shown in Figures 5-19 through 5-23. The relative positions of curves on the ten plots for Calling-In Sticker are remarkably close to the relative positions in Figures 5-14 through 5-18 for Calling-In No-Sticker. The one major and important difference is that all %ΔFMD and %ΔFTP benefits for Calling-In Sticker are between 50 and 70% of the benefits that are calculated for Calling-In No-Sticker. This result means that if vehicles that meet the call-in requirements are given a new two-year certification, the benefits of the call-in activity are reduced by 30 to 50% of those that could have been achieved if the vehicles had not been given a new certification but instead had been required to remain on their existing regular I/M testing schedule.

The figures where Model D was used to calculate the evaluation criteria can be used to estimate the maximum incremental improvement in the benefits produced by adding RSD information to the intervention strategy. A comparison of the benefit of the ΔFMD by D ranking over the ΔFMD by C ranking provides the improvement. For example, Figures 5-19 through 5-23 show that at 5% fleet targeting the %ΔFMD, %ΔFTP HC, %ΔFTP CO, %ΔFTP NX, and FprobDP are -2.8, -0.85, -0.45, -0.44, and 0.33 for vehicle ranking by CS ΔFMD by C and are -3.2, -0.97, -0.50, -0.49, and 0.39 for vehicle ranking by CS ΔFMD by D. These all represent small incremental improvements in benefits caused by adding RSD information.

Figure 5-19. Change in Failed Miles Driven Over 24 Months vs. Percent Fleet Targeting for Calling-In Sticker (Truth ≈ Model D)

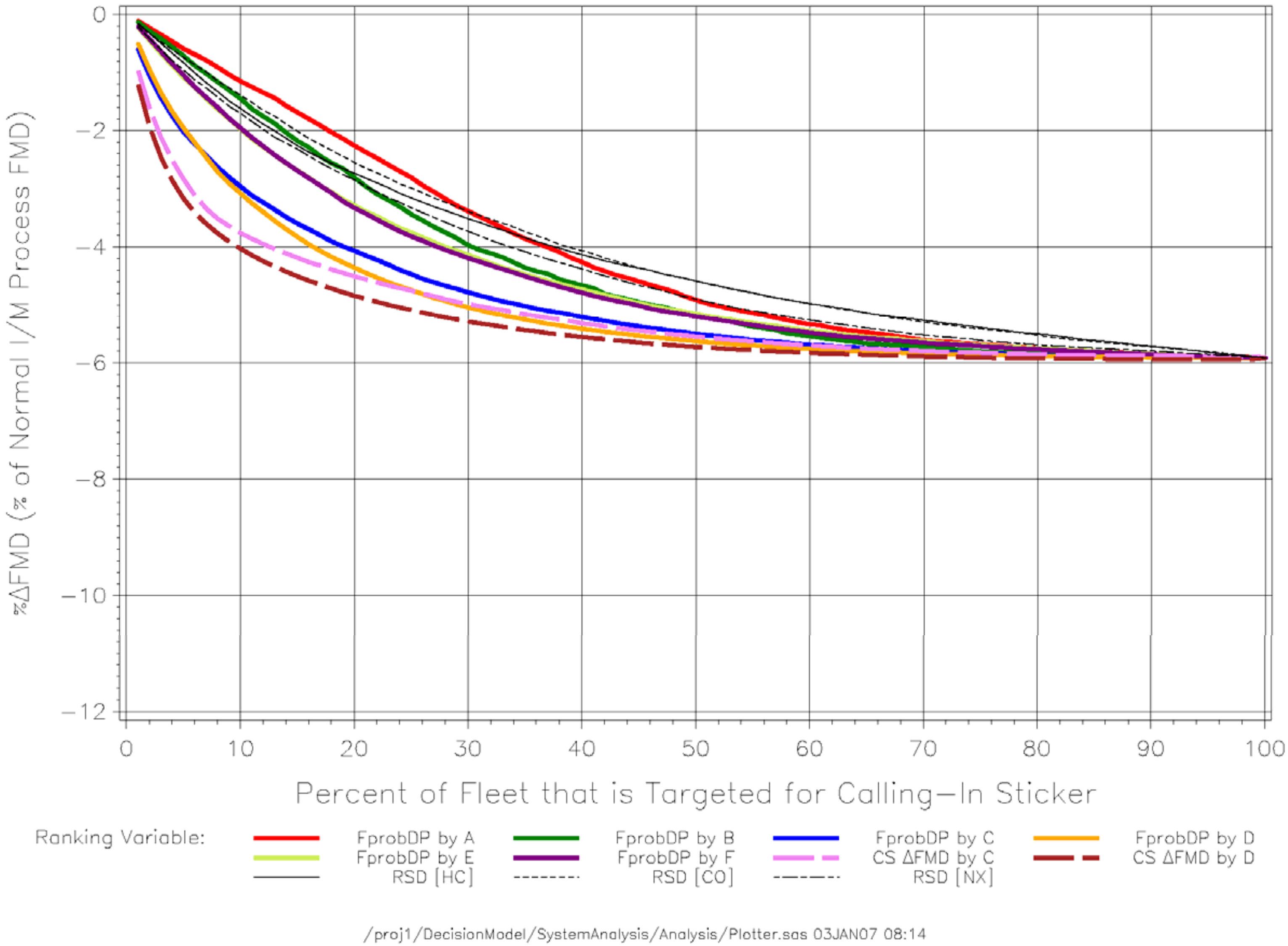


Figure 5-20. Change in FTP HC Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Calling-In Sticker (Truth ≈ Model D)

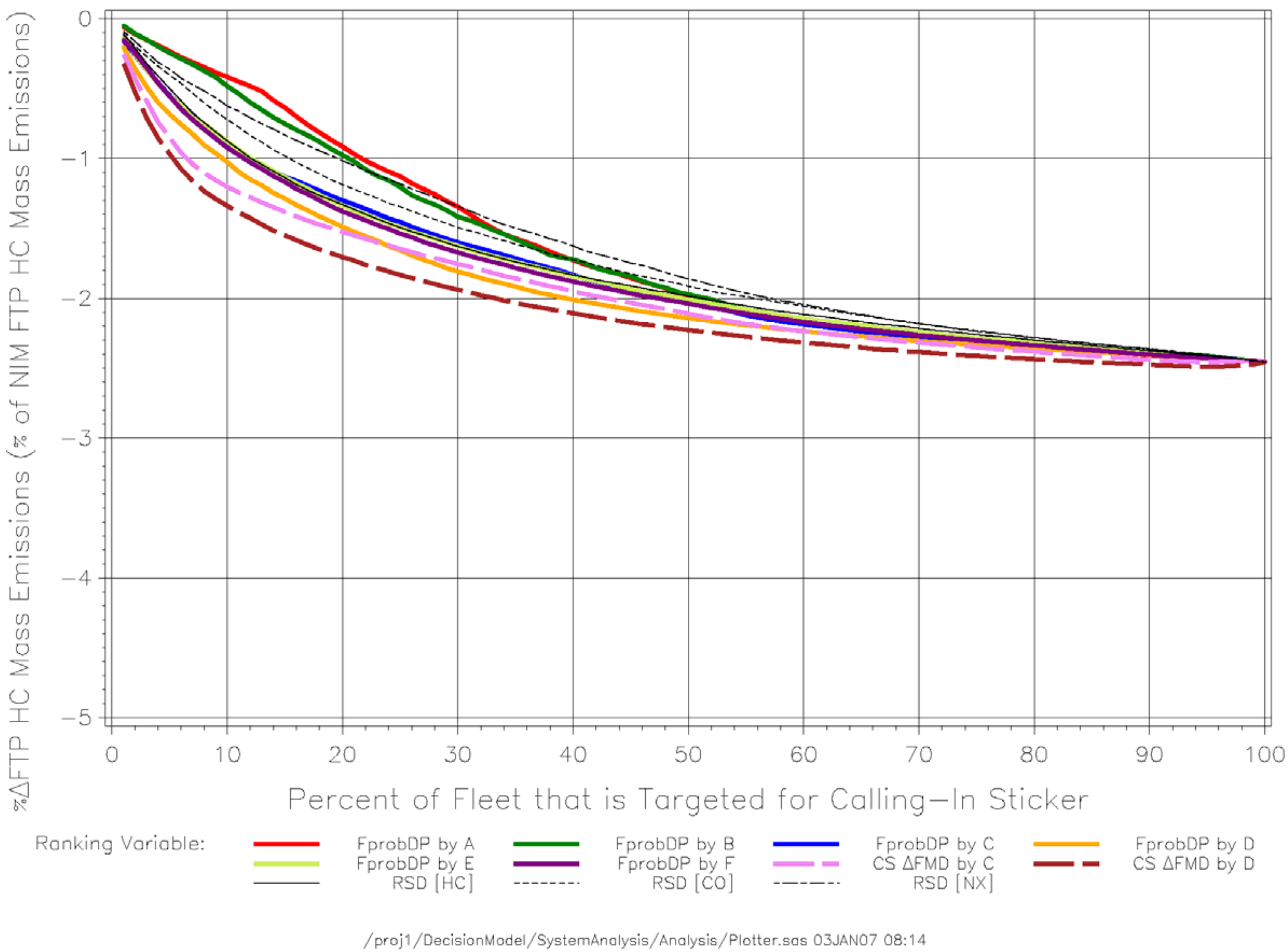


Figure 5-21. Change in FTP CO Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Calling-In Sticker (Truth ≈ Model D)

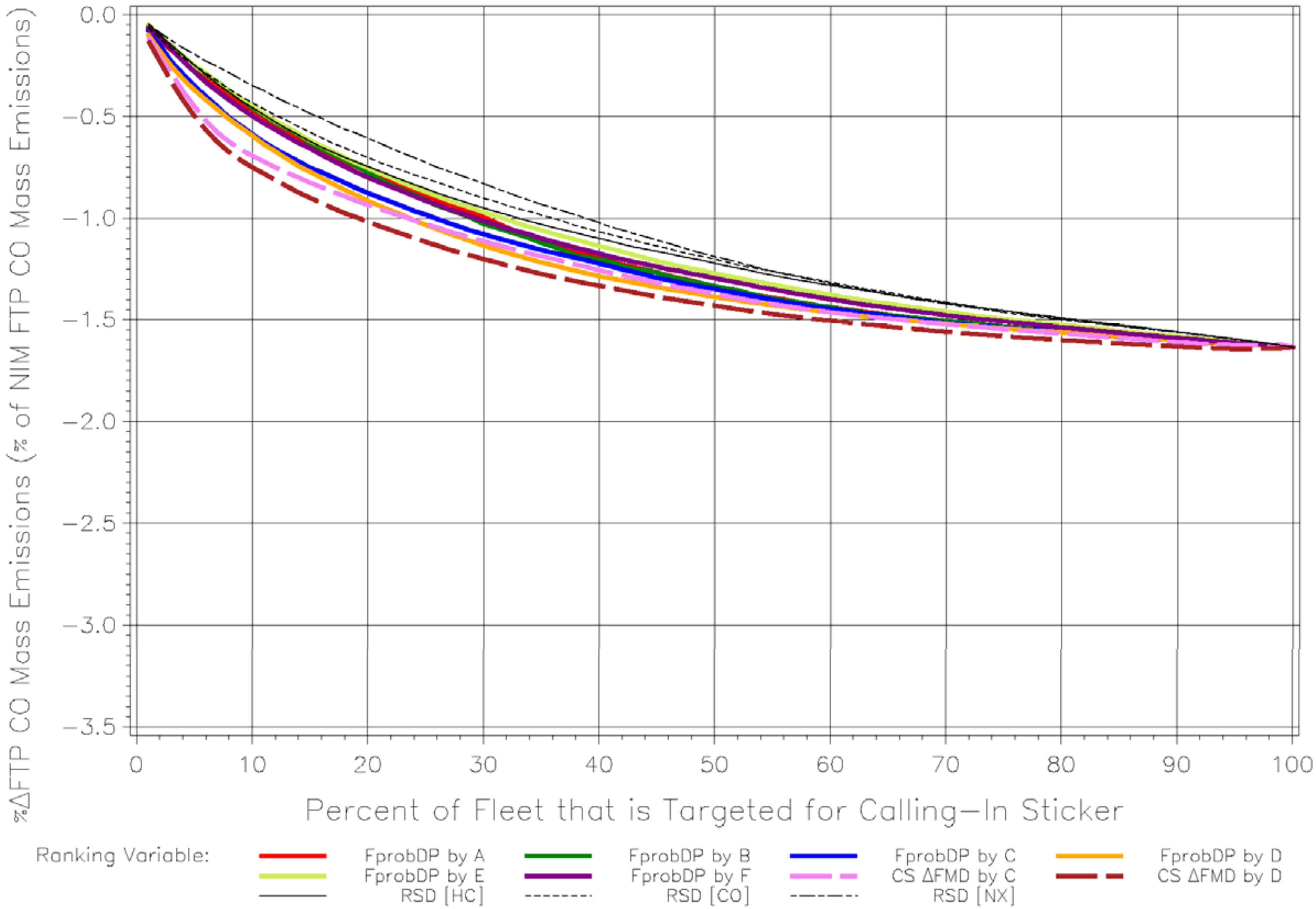


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Figure 5-22. Change in FTP NX Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Calling-In Sticker (Truth ≈ Model D)

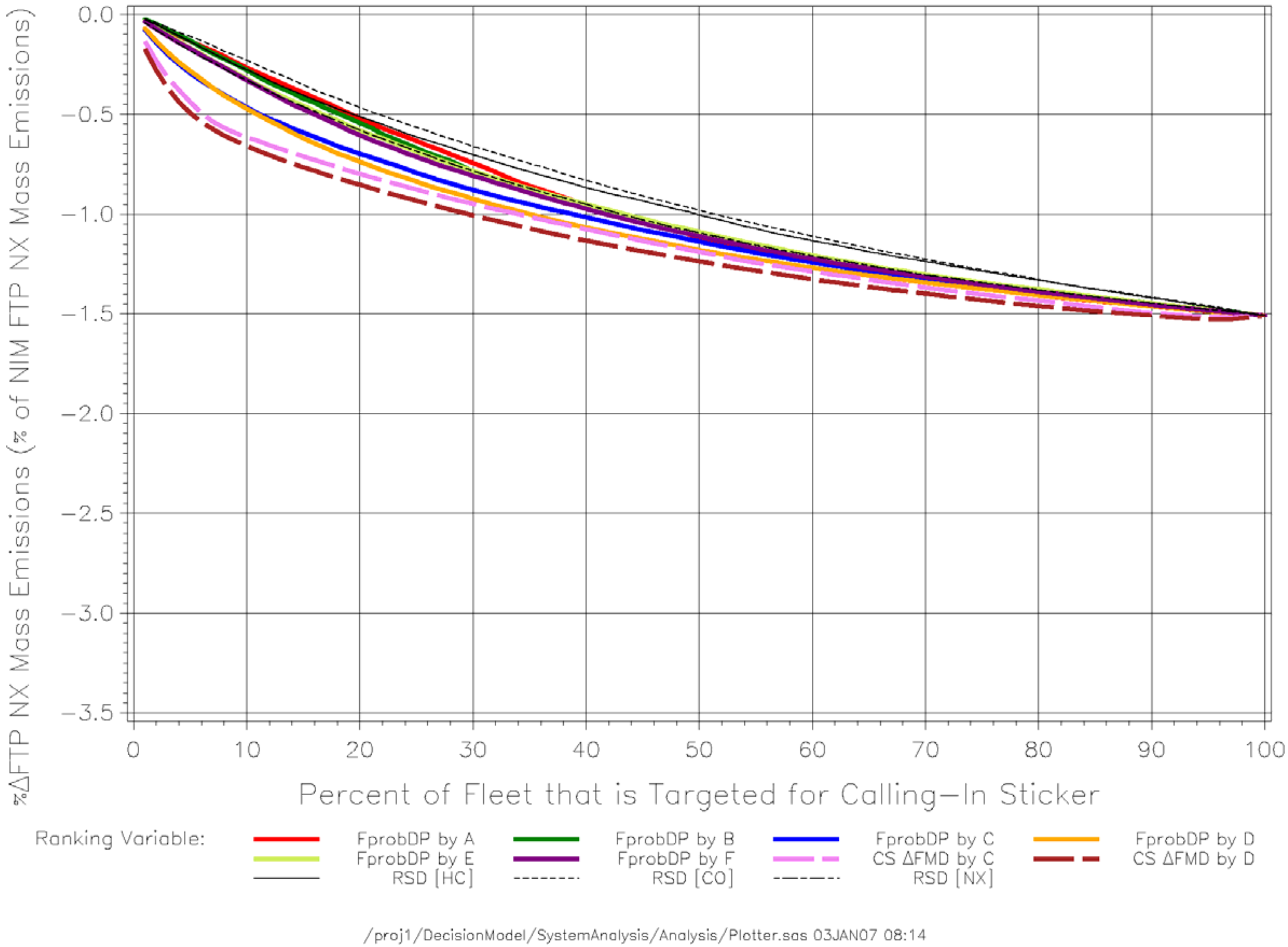
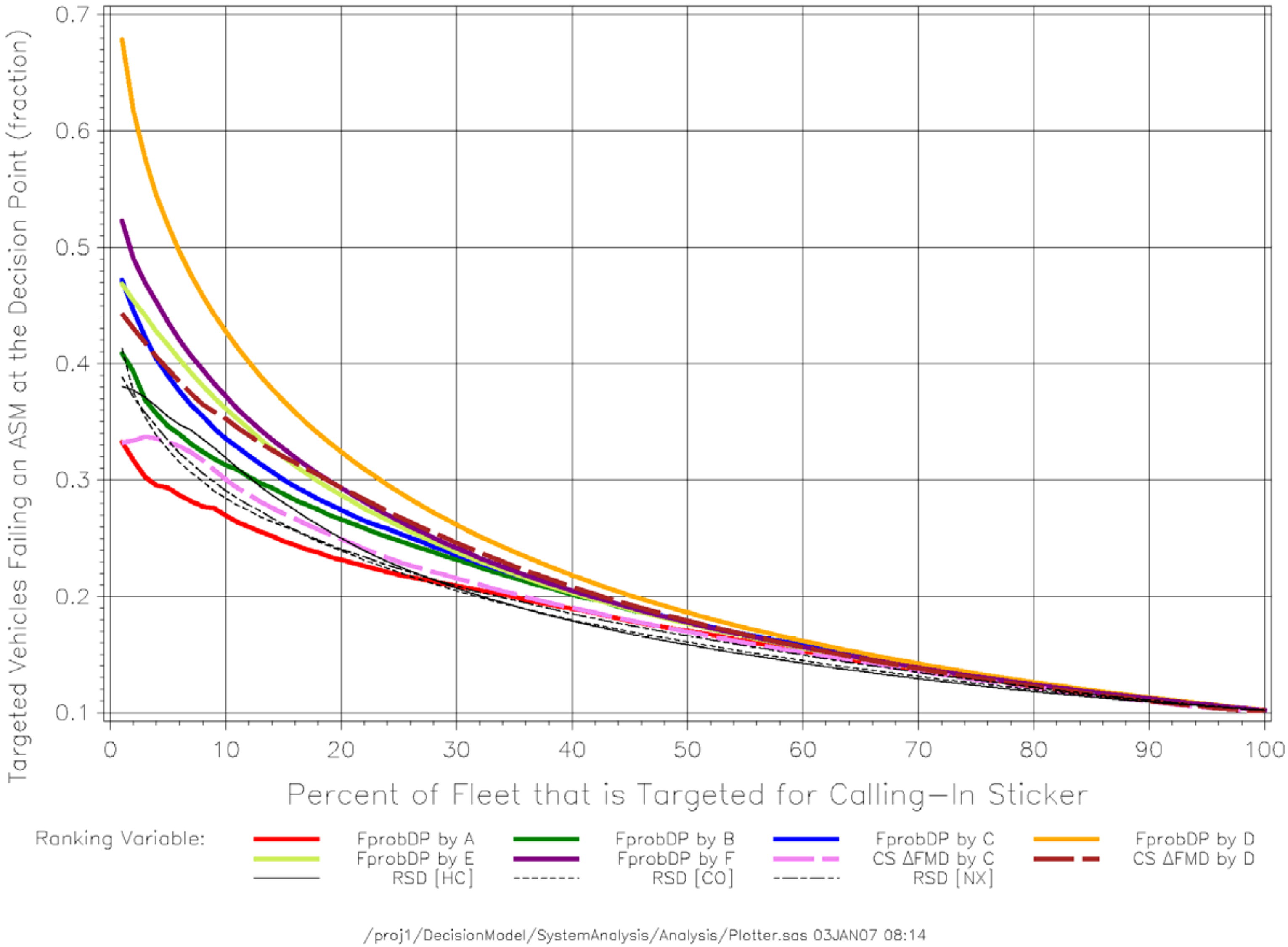


Figure 5-23. Fail Fraction of Targeted Vehicles at the Decision Point vs. Percent Fleet Targeting for Calling-In Sticker (Truth ≈ Model D)



Evaluation of Vehicle Rankings for Scrapping – The evaluation of vehicle rankings for Scrapping takes a somewhat different approach. Suppose that the I/M program has $16 million available biennially to purchase vehicles for scrappage. In addition, suppose that the fleet from which scrappage vehicles will be purchased has the 13,388,069 1976-to-1998-model-year vehicles that were used for the 2004 ARB emissions inventory. The proportional biennial scrapping budget for the 69,629 vehicles in the dataset used in this analysis would be $83,213. If we apply this $83,213 to the purchase of vehicles for each of the 27 different rankings to be evaluated for Scrapping effectiveness, the set of vehicles that are targeted for Scrapping that have the largest decreases in FTP HC, CO, or NX emissions over 24 months after the decision point would be the best vehicle rankings.

We have done this exercise and the results are shown in Table 5-2. The 27 different methods of ranking for scrappage are shown in the first column. The first nine ranking variables are based on the change in FTP HC, CO, or NX emissions per dollar of vehicle value where the estimate of the change in FTP emissions is made by Models C, D, or E. In addition, the change in FTP emissions estimated by these models takes into account all of the specific dependences that Models C, D, and E have and takes into account the probability that individual vehicles will pass or fail a scrappage ASM at the decision point. The next six ranking variables are simply the overall ASM failure probability at the decision point by each of the six models that were developed in this study. For the next six ranking variables, the purchase of the vehicle "buys" failure probability. That is, vehicles are ranked by failure probability at the scrappage ASM test divided by vehicle value. The next three rankings simply rank by measured RSD concentrations. For the last three ranking variables, the purchase of the vehicle "buys" RSD emission concentrations. Vehicles are ranked by measured RSD divided by vehicle value.

The second column shows the number of vehicles that could be purchased for the budget of about $83,213 by starting purchases at the top of each ranking variable list. For this analysis we assumed that the purchase price of the vehicle was equal to the vehicle value. For example, for the ranking by FprobDP by A, 253 vehicles were purchased from the top of that ranking list for the $83,375. On the other hand, for the ranking FprobDP by D only 24 vehicles from the top of the list could be purchased for the same approximate amount.

The fourth, fifth, and sixth columns show the changes in estimated total FTP emissions that would be produced by scrapping the targeted vehicles. These FTP emissions changes are for the 24 months after the decision to call-in the vehicle for a scrappage ASM. In addition, the estimates of ΔFTP assume that when a vehicle is scrapped, 100% of the resulting FTP emissions

Table 5-2. FTP Emissions Changes for 27 Vehicle Ranking Methods for Scrapping (Truth ≈ Model D)

Ranking Variable	Number of Vehicles Targeted of 69,629	Dollars Spent for Buying Vehicles for Scrapping	ΔFTP (g_{Inv}/24 months)			Average ΔFTP/$ (g_{Inv}/24 months/$)			
			HC	CO	NX	HC	CO	NX	HC+NX
ΔFTP HC/$ by C	314	$83,253	-12,516,336	-151,798,523	-6,631,780	-150	-1,823	-80	-230
ΔFTP CO/$ by C	320	$83,045	-13,198,056	-155,341,286	-6,752,642	-159	-1,871	-81	-240
ΔFTP NX/$ by C	295	$83,240	-12,506,423	-145,267,145	-6,848,342	-150	-1,745	-82	-233
ΔFTP HC/$ by D	246	$83,089	-14,016,518	-168,800,723	-6,809,722	-169	-2,032	-82	-251
ΔFTP CO/$ by D	237	$83,673	-14,542,100	-157,788,231	-6,751,275	-174	-1,886	-81	-254
ΔFTP NX/$ by D	228	$82,984	-12,954,377	-145,486,075	-7,312,966	-156	-1,753	-88	-244
ΔFTP HC/$ by E	210	$83,018	-12,631,555	-152,157,243	-5,973,602	-152	-1,833	-72	-224
ΔFTP CO/$ by E	218	$83,290	-13,029,721	-153,688,706	-6,449,534	-156	-1,845	-77	-234
ΔFTP NX/$ by E	205	$82,989	-12,134,624	-137,617,978	-6,735,438	-146	-1,658	-81	-227
FprobDP by A	253	$83,375	-7,323,401	-82,152,494	-4,304,869	-88	-985	-52	-139
FprobDP by B	75	$83,414	-2,697,585	-29,035,406	-1,871,146	-32	-348	-22	-55
FprobDP by C	33	$82,718	-741,078	-5,524,248	-659,531	-9	-67	-8	-17
FprobDP by D	24	$82,976	-1,591,789	-11,714,578	-1,079,165	-19	-141	-13	-32
FprobDP by E	36	$82,073	-1,737,596	-10,942,022	-828,276	-21	-133	-10	-31
FprobDP by F	45	$82,448	-2,859,259	-23,739,376	-1,491,198	-35	-288	-18	-53
FprobDP/$ by A	439	$83,358	-14,511,588	-164,492,977	-7,474,848	-174	-1,973	-90	-264
FprobDP/$ by B	339	$83,194	-12,772,328	-147,925,131	-6,611,555	-154	-1,778	-79	-233
FprobDP/$ by C	317	$83,297	-12,502,403	-147,096,101	-6,584,360	-150	-1,766	-79	-229
FprobDP/$ by D	252	$83,346	-13,790,866	-161,469,098	-6,999,342	-165	-1,937	-84	-249
FprobDP/$ by E	246	$82,989	-13,552,126	-156,991,089	-6,762,240	-163	-1,892	-81	-245
FprobDP/$ by F	285	$83,124	-14,445,026	-166,161,702	-7,321,364	-174	-1,999	-88	-262
RSD [HC]	57	$83,479	-2,910,062	-23,160,086	-1,549,844	-35	-277	-19	-53
RSD [CO]	66	$83,356	-3,651,814	-35,350,672	-1,249,701	-44	-424	-15	-59
RSD [NX]	72	$84,010	-2,053,029	-16,182,059	-1,498,628	-24	-193	-18	-42
RSD [HC]/$	119	$82,965	-6,110,953	-63,712,156	-3,051,177	-74	-768	-37	-110
RSD [CO]/$	181	$82,903	-9,361,865	-117,806,702	-3,674,133	-113	-1,421	-44	-157
RSD [NX]/$	215	$83,312	-7,854,614	-82,326,162	-5,734,668	-94	-988	-69	-163

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produced by that vehicle is realized. Finally, the last four columns show the average emission reduction cost efficiency of scrapping the targeted vehicles. The calculation of the FTP emissions for the last seven columns of the table is based on Model D.

Examination of the table indicates that the largest emissions reductions and, therefore, the largest scrappage efficiencies are obtained by the rankings using ΔFTP/$ and FprobDP/$. Judging by the table's last column, which gives the vehicle value effectiveness of emissions reduction, the best single performing ranking is perhaps FprobDP/$ by A. For $83,358 spent to scrap 439 vehicles, estimated FTP HC, CO, and NX were reduced by 14.5, 164, and 7.5 metric tons over 24 months. This is quite an amazing result because the inputs to vehicle rankings by FprobDP/$ by A are just the model year and the estimated vehicle value as defined by the vehicle make and the vehicle type (car vs. truck). This ranking variable for Scrapping appears to be at least as good as any other method – even those that use RSD measurements and/or VID history.

While FprobDP/$ by A is possibly the best Scrapping ranking variable, fourteen others are very strong competitors with HC + NX vehicle value effectivenesses in the range of -224 to -262 g/24month/$. The feature common to all of these strong performers is the presence of the estimated vehicle value in the denominator of the ranking variable. Without vehicle value, the six Fprob models have poor performance, but with vehicle value, they have excellent performance. However, having vehicle value in the ranking variable is not a guarantee of excellent performance. For example, without vehicle value the RSD concentrations have poor performance. When vehicle value is used with the RSD concentrations (RSD/$), the performances improve, but they are still mediocre. It is the combining of the three individual RSD measurements using Models D, E, or F plus the use of the vehicle value that produces a high-performance RSD-containing ranking variable. Still, those RSD-containing ranking methods for Scrapping are no better at reducing FTP mass emissions than the FprobDP/$ by A method, which uses only model year and vehicle value.

Estimating the incremental benefits of adding RSD information to other information to rank vehicles for Scrapping is a key goal of this study. This can be quantified by comparing the ΔFTP/$ by D rankings with the ΔFTP/$ by C rankings. Since the FTP emissions estimates in the last seven columns of Table 5-2 were based on calculations using the Model D estimates, the ΔFTP/$ by D rankings have the maximum possible advantage over the ΔFTP/$ by C rankings. Yet, we see from Table 5-2 that the Model D rankings are only marginally superior to the Model C rankings. This indicates to us that it is unlikely that the cost of an RSD program could be justified for ranking vehicles for Scrapping alone by Model D, which requires RSD measurements, when similarly performing rankings by Model C, which is based on VID history, produces rankings that are nearly as efficient. And, of course, the FprobDP/$ by A ranking produces the highest efficiency ranking for Scrapping that we have found, and it uses quite simple inputs – model year and vehicle value.

The evaluation of the different ranking variables for identifying Scrapping candidates which was shown in Table 5-2 gives the results only for the case where the scrappage vehicle budget for two years was $16 million. We would like to generalize the results shown in the table for other scrappage vehicle budgets. We will do this analysis graphically to show that the relative performance qualities of the 27 different ranking methods shown in Table 5-2 are more or less independent of the size of the scrappage vehicle budget.

Figures 5-24 through 5-28 show the %ΔFMD, %ΔFTP (HC, CO, and NX), and FprobDP for the 27 different Scrapping vehicle rankings as a function of the percent of the fleet that is targeted for Scrapping. From the number of vehicles shown in the second column of Figure 5-2 that were targeted for Scrapping, we can conclude that the Scrapping targeting fraction for Table 5-2 ranged from 0.03% to 0.63%. For a given scrappage vehicle purchase budget, more vehicles can be scrapped if the vehicle ranking method selects lower-valued vehicles. Therefore, when we look at the performance curves for Figures 5-24 through 5-28, we need to realize that even though the fleet targeting percentage might be constant, the cost of purchasing the vehicles to achieve that fleet targeting percentage can be quite different.

If we were going to select vehicles for scrappage based on a desired fleet targeting percentage, we would use Figures 5-24 through 5-28 to make judgments about the performance. Figure 5-25 shows that the biggest changes in %ΔFTP HC are produced by ΔFTP HC/$ by D (thick dashed gray). Figure 5-26 shows that the largest changes in %ΔFTP CO are produced by ΔFTP CO/$ by E (thick dashed yellow). Figure 5-27 shows that the largest changes in %ΔFTP NX are produced by FprobDP by D (thick solid orange). Figure 5-28 shows the fail fraction of the targeted vehicles that would be observed for a scrappage ASM test. The highest fail fraction is observed for FprobDP by D (thick solid orange).

Since the curves in Figures 5-24 through 5-28 do not cross each other substantially, the relative performances of the different ranking methods are approximately the same for any fleet targeting percentage.

The cumulative value of vehicles from the top of each different ranking is shown in Figure 5-29 as a function of the fleet targeting percentage. For example, for FprobDP by D (thick solid orange) has the steepest slope, which means that this method is targeting more valuable vehicles, and FprobDP/$ by A (thin solid red) has the lowest slope, which means that this method is targeting less valuable vehicles. The information in Figure 5-29 can be used to convert Figures 5-24 through 5-28 into performance curves based on the cumulative probable value of the vehicles that are targeted for Scrapping. These plots are shown in Figures 5-30 through 5-34.

Figure 5-24. Change in Failed Miles Driven Over 24 Months vs. Percent Fleet Targeting for Scrapping (Truth ≈ Model D)

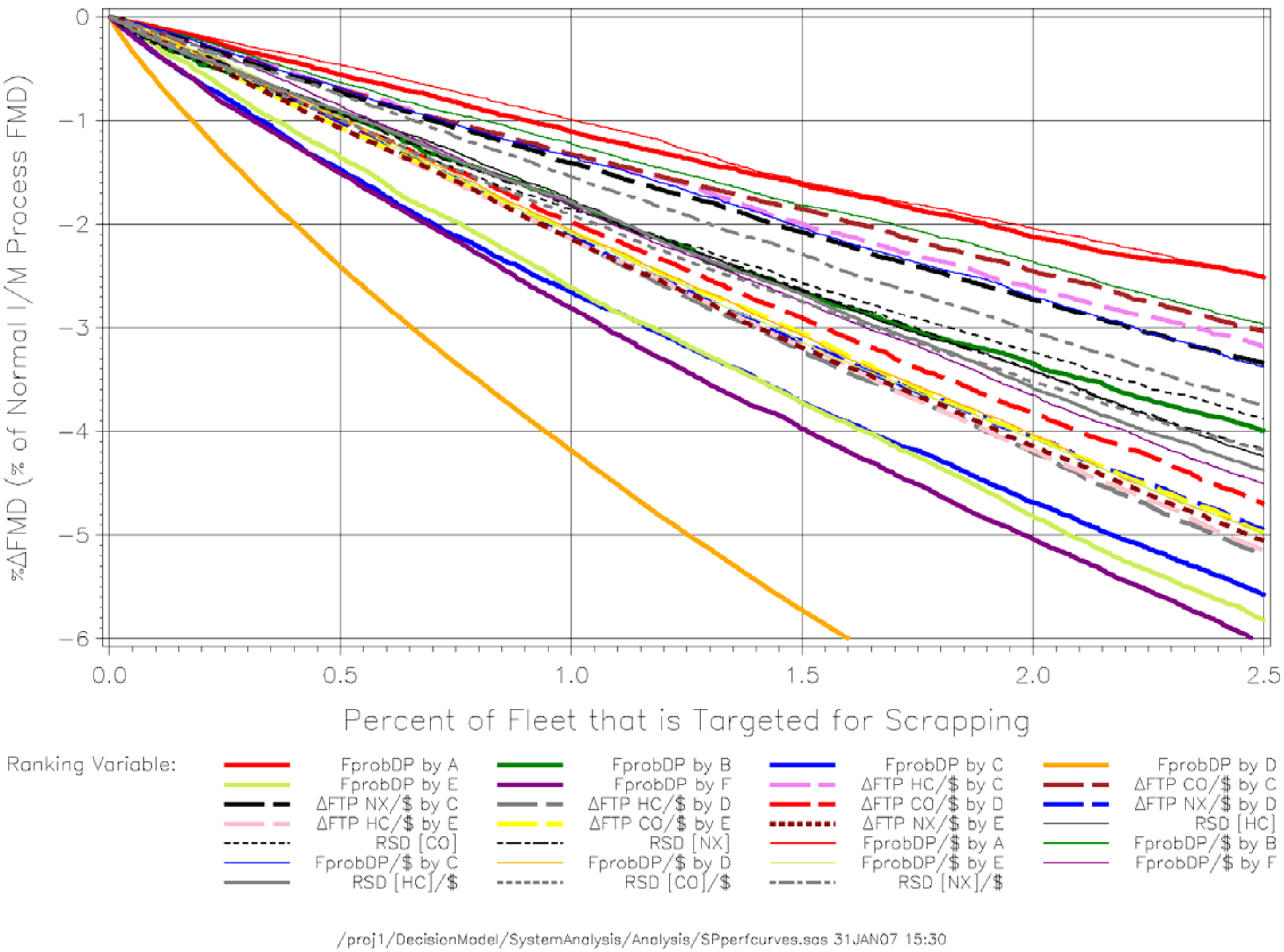

Figure 5-25. Change in FTP HC Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Scrapping (Truth ≈ Model D)

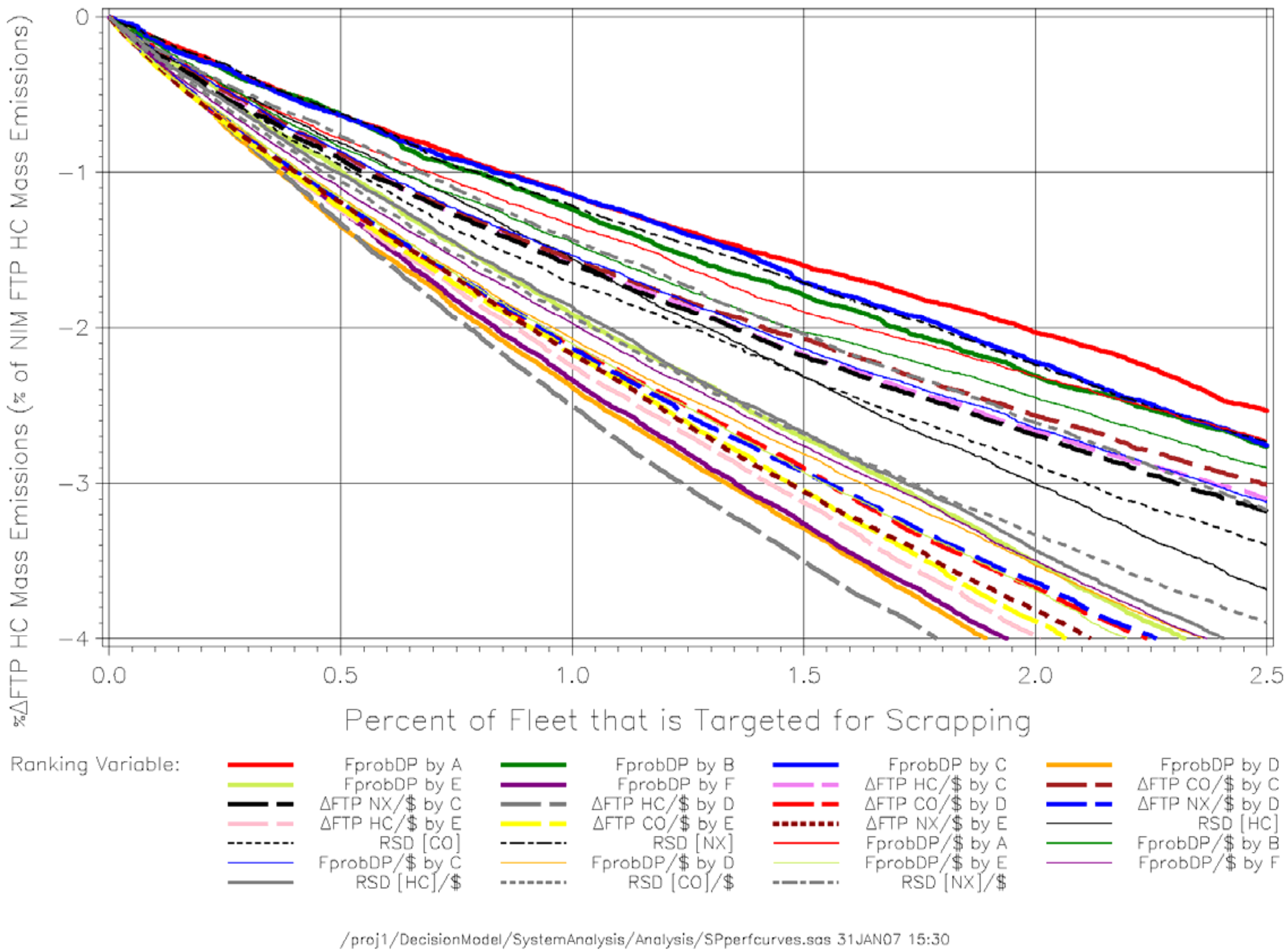

Figure 5-26. Change in FTP CO Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Scrapping (Truth ≈ Model D)

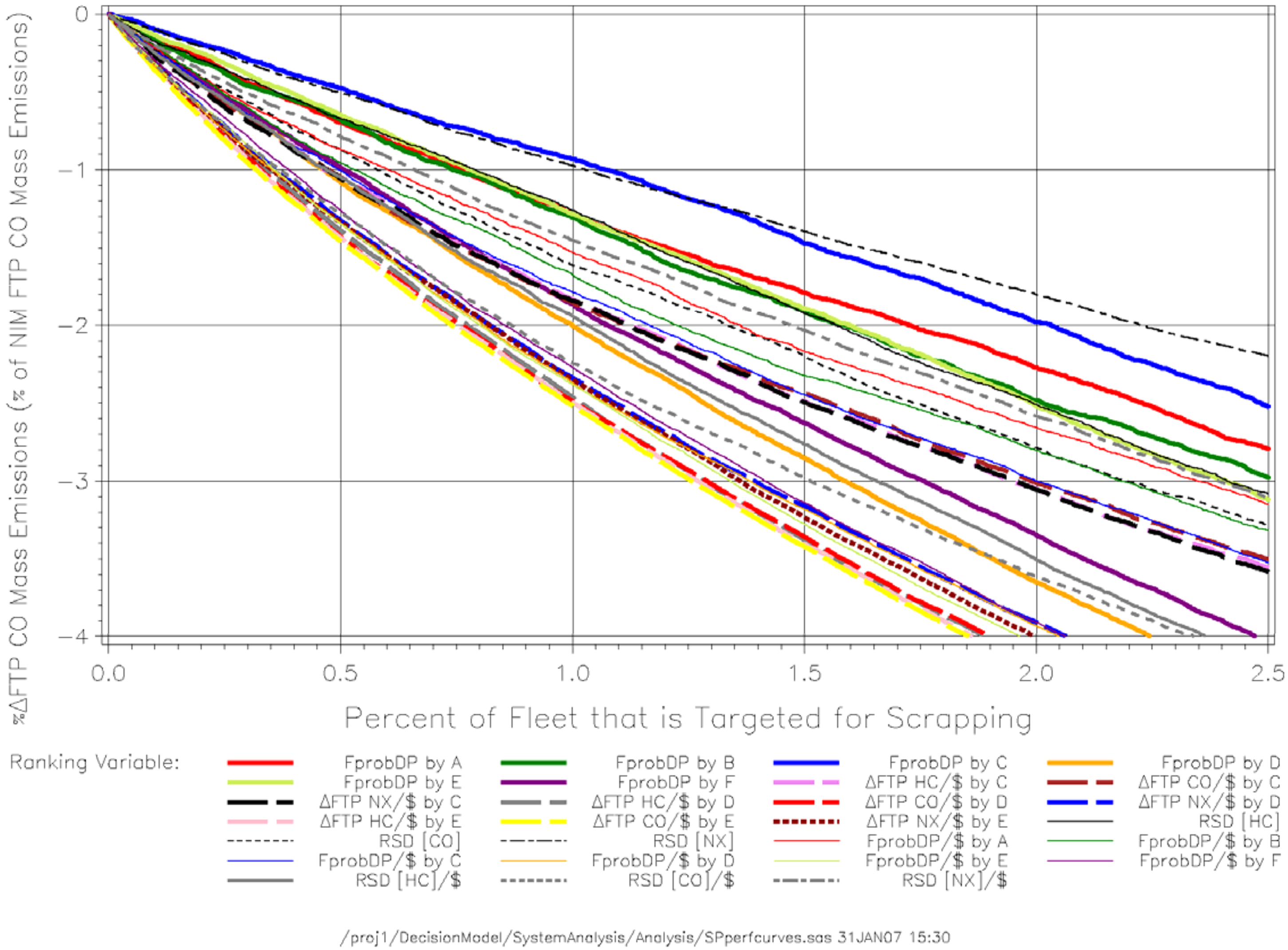

Figure 5-27. Change in FTP NX Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Scrapping (Truth ≈ Model D)

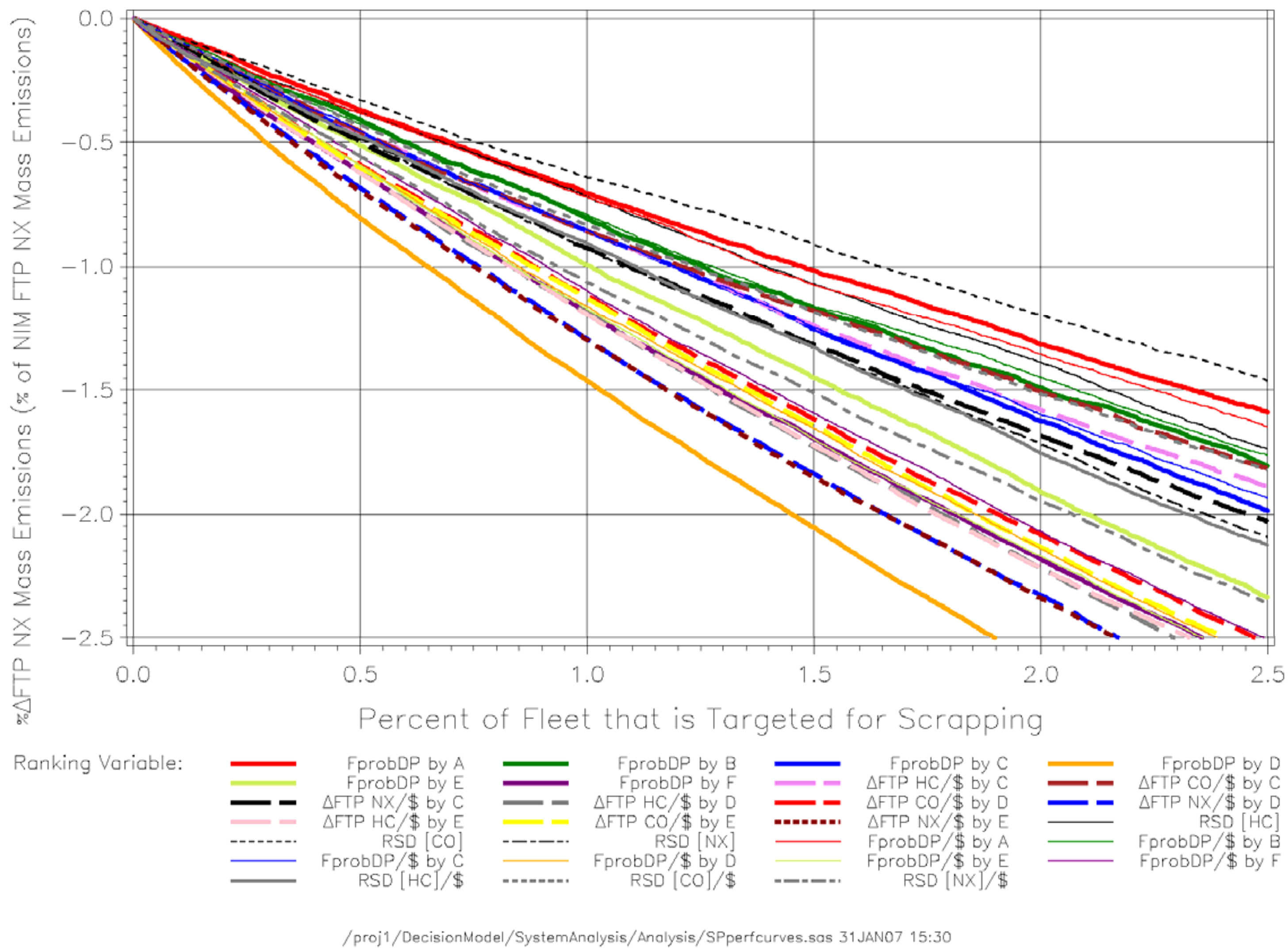

Figure 5-28. Fail Fraction of Targeted Vehicles at the Decision Point vs. Percent Fleet Targeting for Scrapping (Truth ≈ Model D)

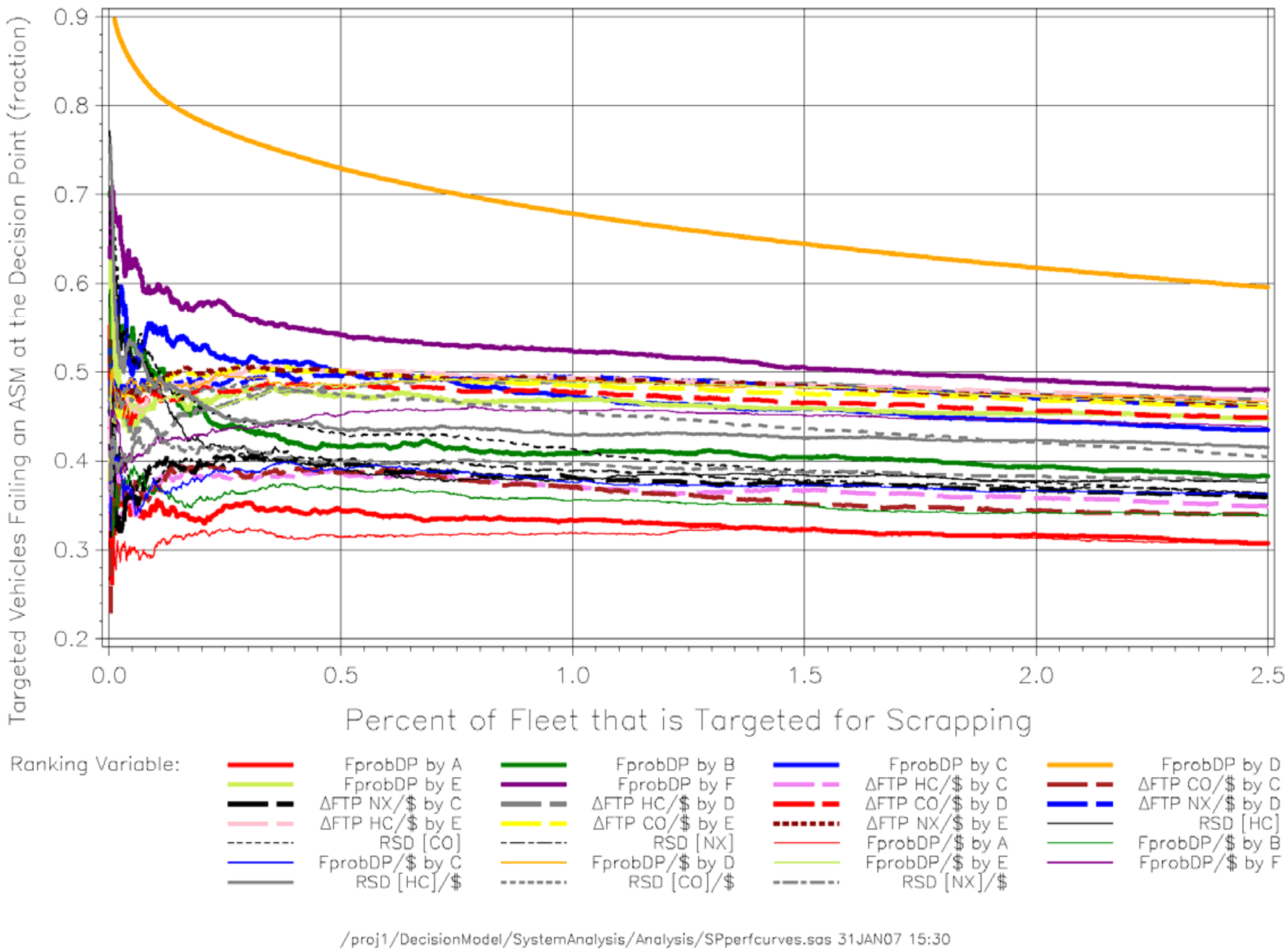

Figure 5-29. Cumulative Probable Value of Targeted Vehicles vs. Percent Fleet Targeting for Scrapping (Truth ≈ Model D)

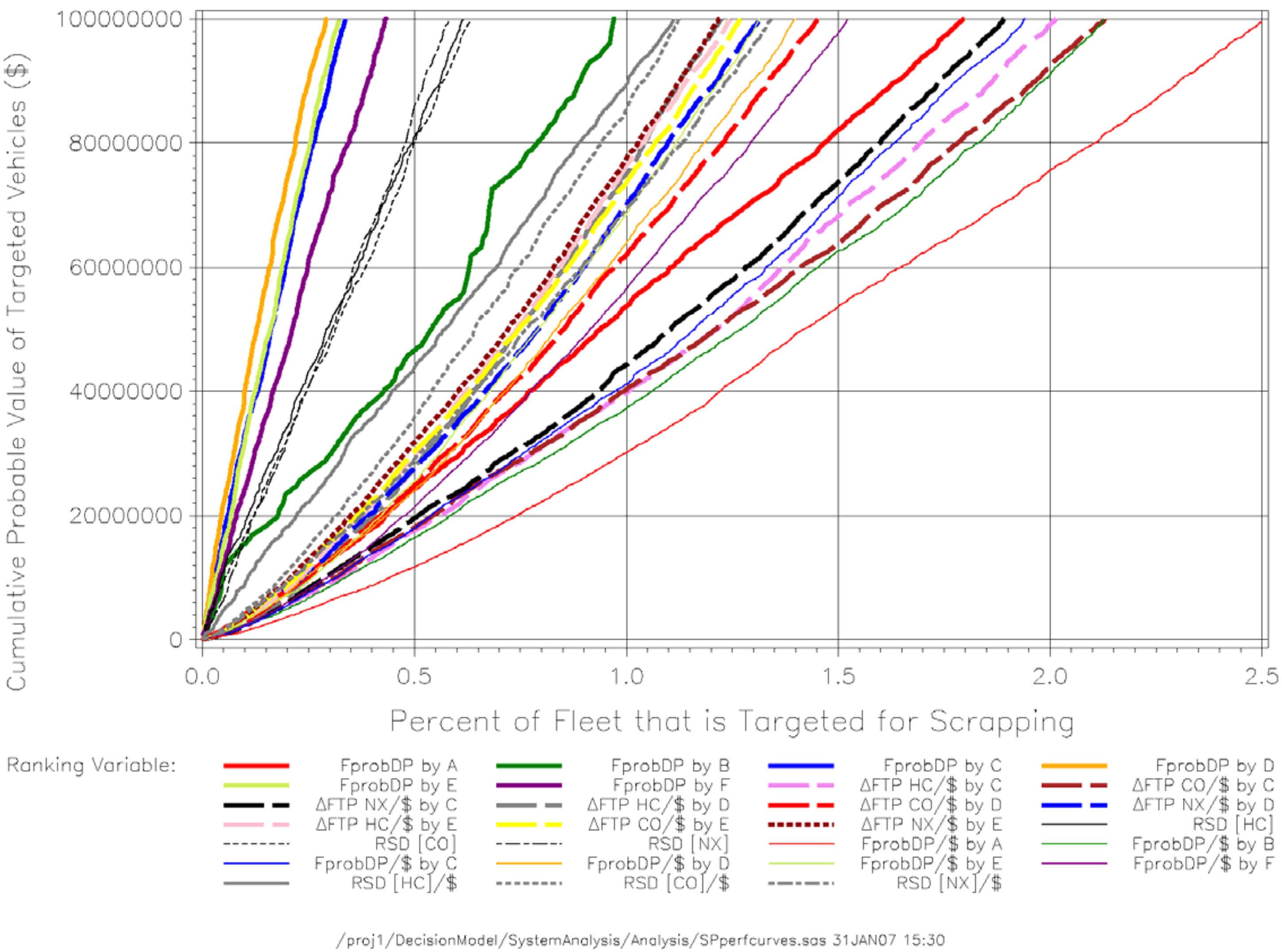

Figure 5-30. Change in Failed Miles Driven Over 24 Months vs. Probable Value of Targeted Vehicles for Scrapping (Truth ≈ Model D)

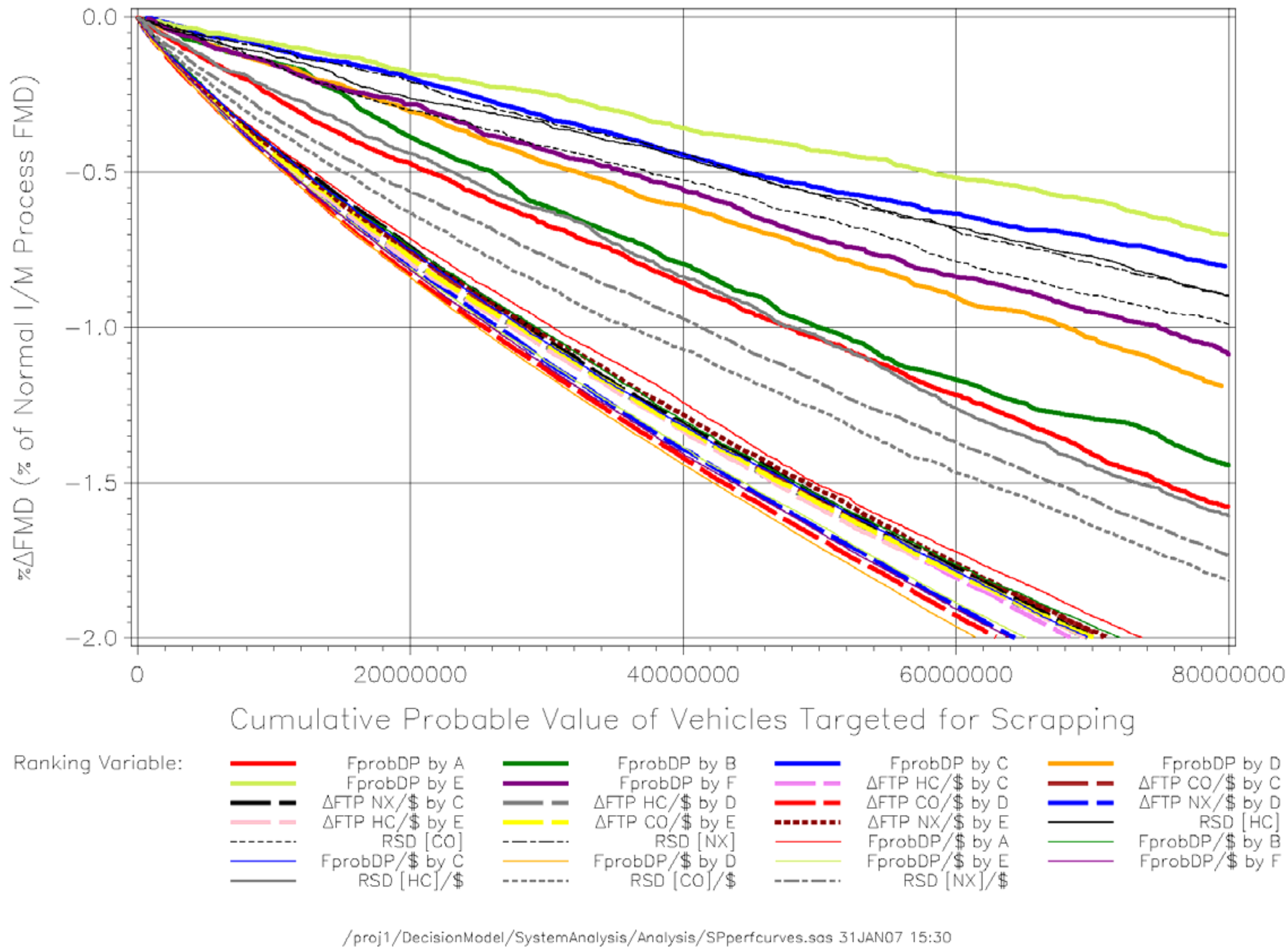

Figure 5-31. Change in FTP HC Mass Emissions Over 24 Months vs. Probable Value of Targeted Vehicles for Scrapping (Truth ≈ Model D)

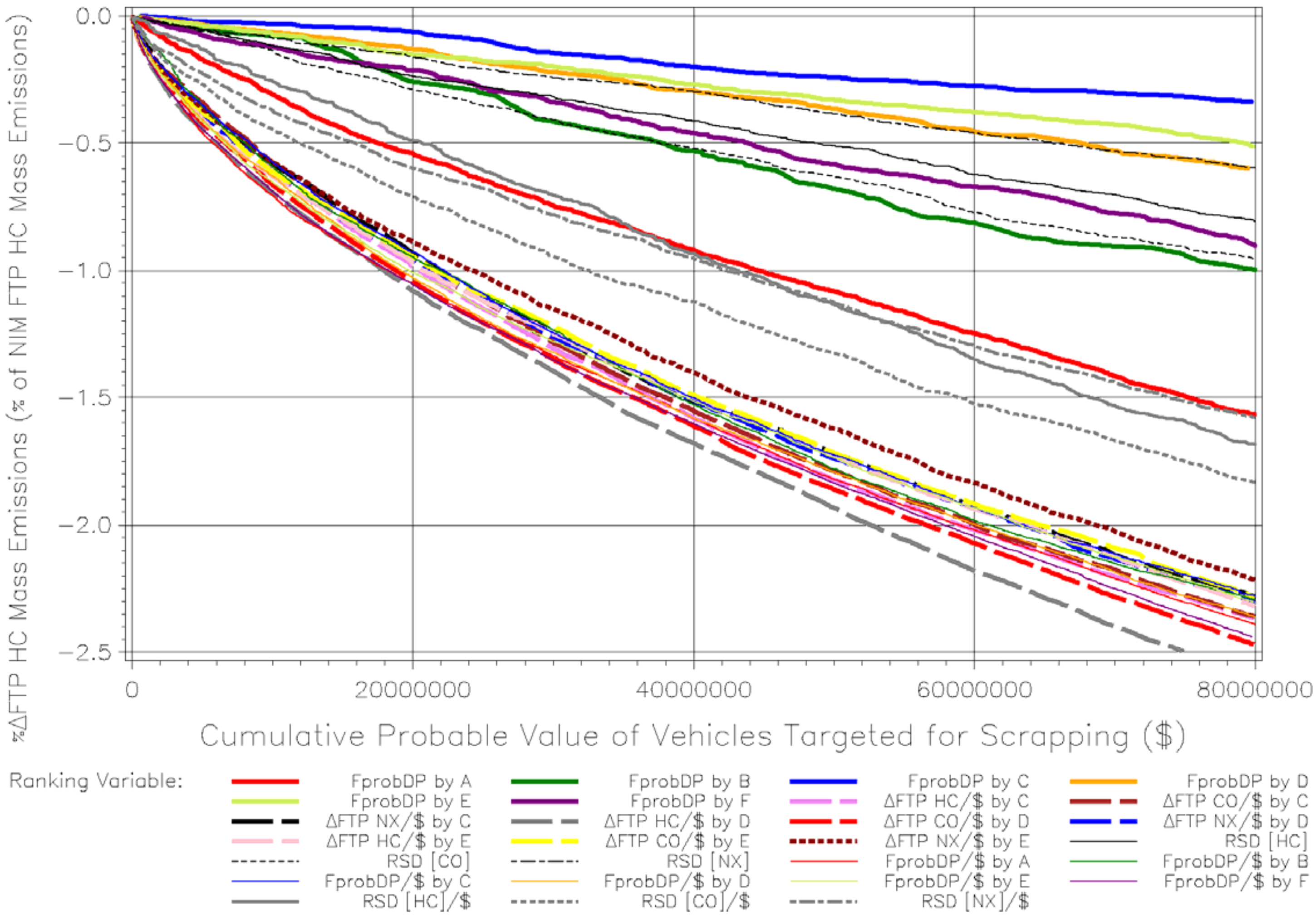

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Figure 5-32. Change in FTP CO Mass Emissions Over 24 Months vs. Probable Value of Targeted Vehicles for Scrapping (Truth ≈ Model D)

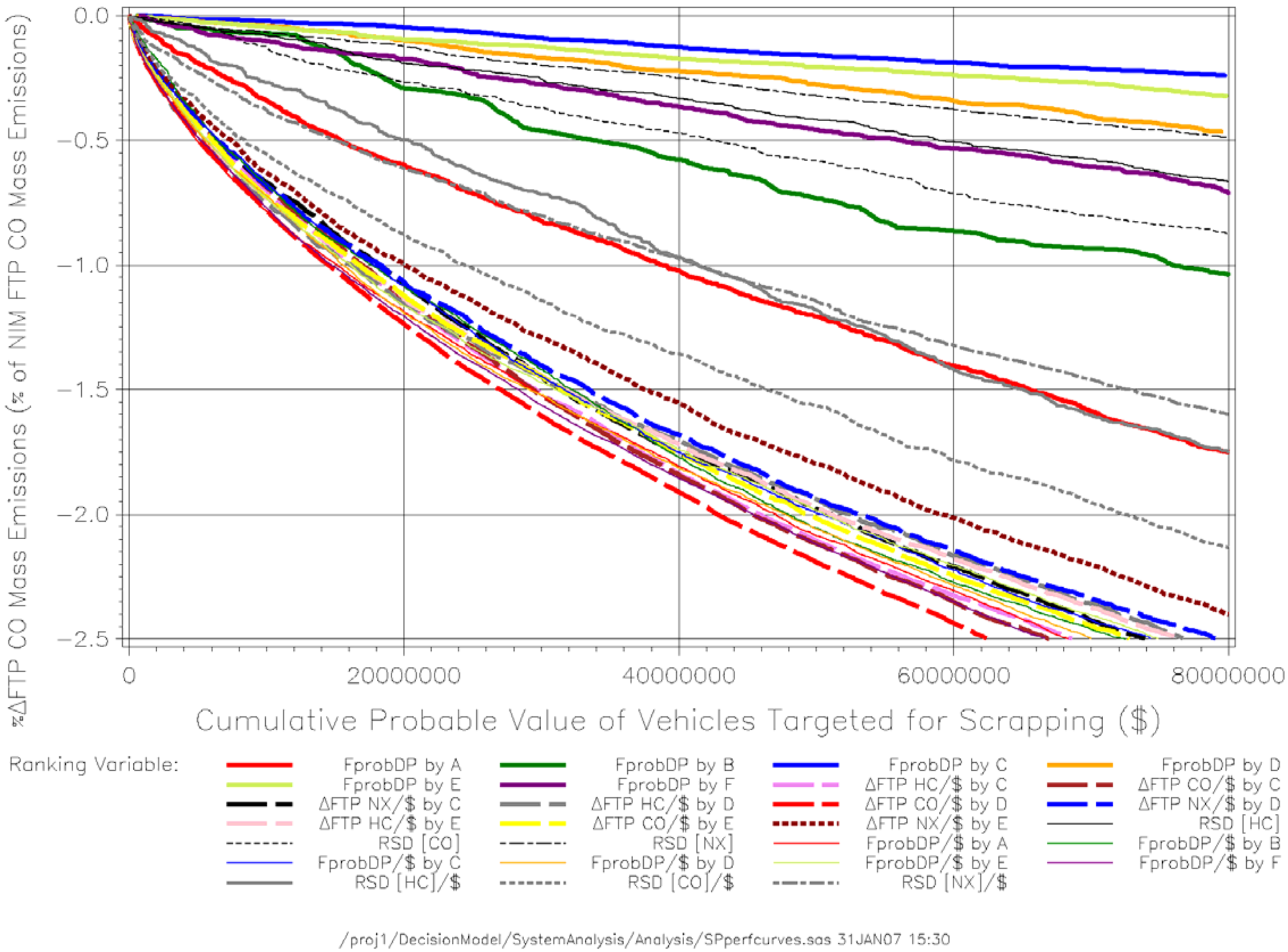


Figure 5-33. Change in FTP NX Mass Emissions Over 24 Months vs. Probable Value of Targeted Vehicles for Scrapping (Truth ≈ Model D)

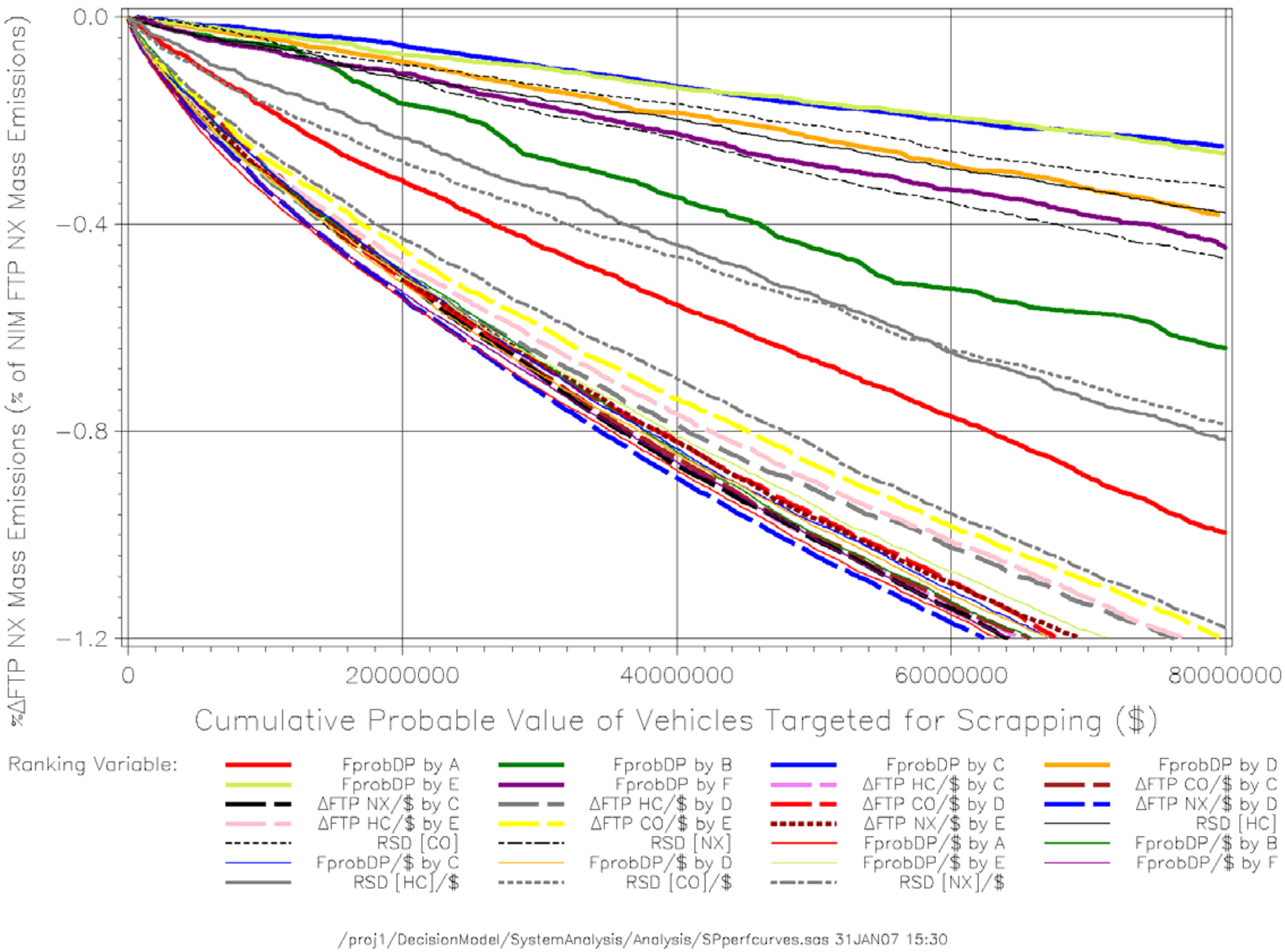
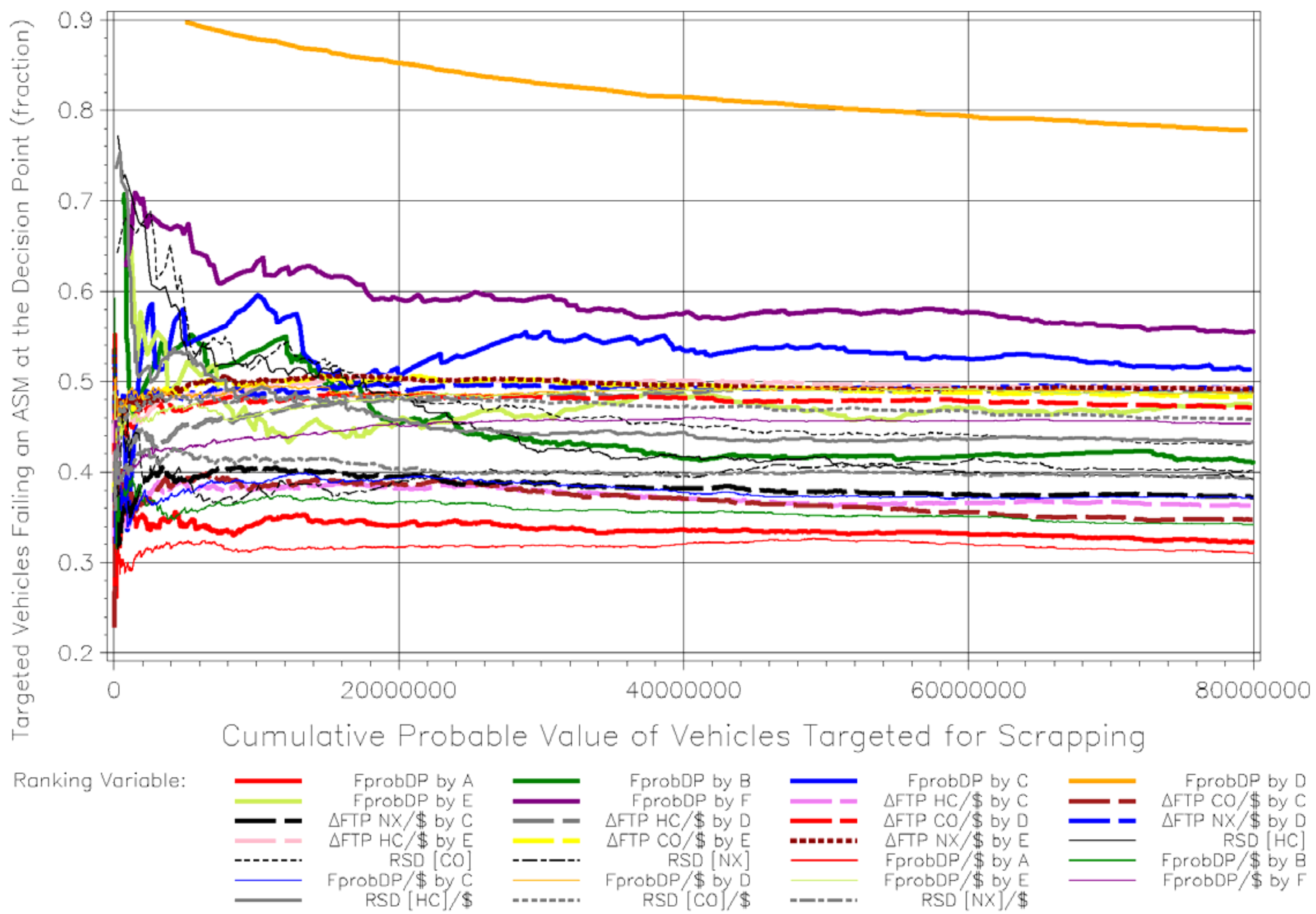


Figure 5-34. Fail Fraction of Targeted Vehicles at the Decision Point vs. Probable Value of Targeted Vehicles for Scrapping (Truth ≈ Model D)



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Figures 5-30 through 5-34 provide an entirely different view of the relative performance of the Scrapping ranking variables than do Figures 5-24 through 5-28. These new figures show the relative performance of the ranking variables at a constant scrappage vehicle purchase budget. In each of the figures, the performance curves for different ranking variables tend not to cross each other. Thus, the relative positions of the performances remain about the same and are independent of the size of the purchase budgets. This means that the relative performance of the ranking variables as shown in Table 5-2 will be about the same for vehicle purchase budgets that are different than the $16 million/24months used to generate Table 5-2.

Figure 5-30 shows the effects of the different ranking variables on %ΔFMD. Figures 5-31, 5-32, and 5-33 show the effects of the different ranking variables on the %ΔFTP HC, CO, and NX. Examination of these four figures shows a remarkable similarity in the order and grouping of performance for the different ranking methods. The 12 poorer performing ranking variables are the uppermost 12 curves on each figure. They include the three RSD concentration rankings (thin black lines), the three RSD concentration with vehicle value rankings (medium gray lines), FprobDP by F (thick solid purple) which combines the three individual RSD concentration readings, FprobDP by E (thick solid light-green) which combines the three individual RSD concentration readings and ASM cutpoints, FprobDP by D (thick solid orange) which uses RSD measurements and VID history, FprobDP by C (thick solid blue) which uses only VID history, FprobDP by B (thick solid green) which uses vehicle description, and FprobDP by A (thick solid red) which uses only model year. All of the other 15 ranking variables form a high performance cluster in the bottom curves of Figures 5-30, 5-31, 5-32, and 5-33. Any of the ranking variables that are in this cluster of 15 would produce the largest decreases in failed miles driven and FTP mass emissions over the 24 months after the vehicle was scrapped.

However, there is another consideration. When the vehicle is called in at the Decision Point for its scrappage ASM, we want a large fraction of the vehicles to fail the scrappage ASM test. Figure 5-34 shows the fail fraction of the targeted vehicles at the Decision Point as a function of the cumulative probable value of the vehicles targeted. The plot shows that across this wide range of the scrappage vehicle purchase budget from 0 to $80 million over two years, the fail fractions at the decision point do not cross over each other to a large degree. This means that the fail fraction for the different ranking methods have more or less the same relative position with regard to fail fraction at the decision point.

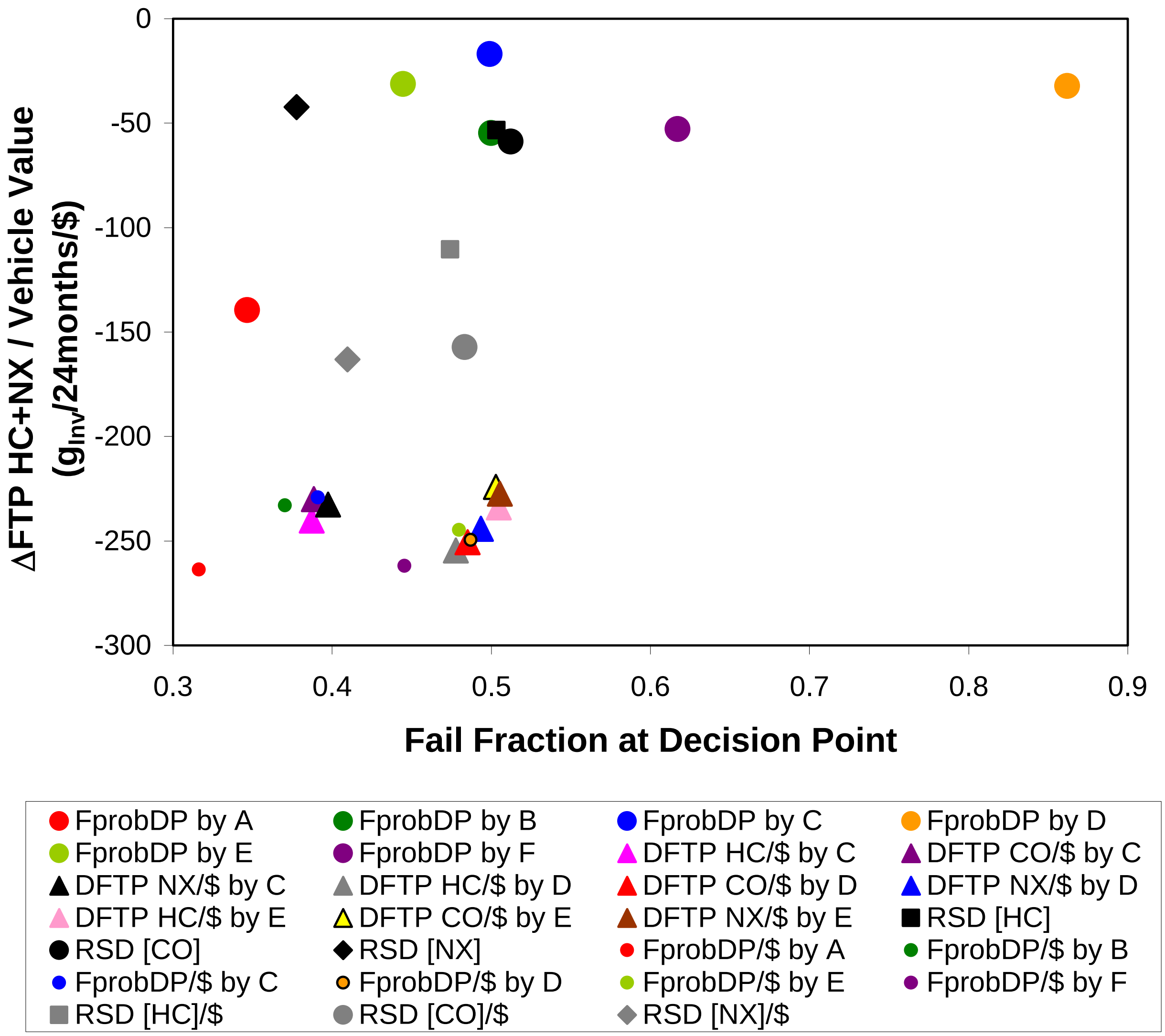
The most attractive vehicle ranking method for Scrapping would produce large decreases in FTP HC+NX emissions for each dollar of vehicle value and would have high fail fractions at the decision point. Since we know that the relative attractiveness of ΔFTP HC+NX per dollar of vehicle value as shown in Table 5-2 and the relative fail fractions at Decision Point as shown in Figure 5-34 tend not to rearrange for different sizes of scrappage vehicle purchase budgets, we can simply use the results from the $16 million biennial scrappage budget to infer which vehicle ranking methods would be attractive for almost any scrappage budget.

Figure 5-35 shows the ΔFTP HC+NX emissions values per dollar of vehicle value plotted against the fraction of vehicles that fail at the Decision Point for the $16 million biennial scrappage vehicle purchase budget. Data points at the top of the plot represent ranking methods that do not decrease FTP HC+NX emissions a great deal. The 15 data points at the bottom of the plot are the vehicle ranking methods that select vehicles that make large decreases in FTP HC+NX emissions. These are the same methods that produce the bottom clusters of lines in Figures 5-30 through 5-33. Data points on the left side of the plot represent those methods that rank vehicles with lower fail fractions at the decision point for the vehicles that are called in for scrappage ASM tests. Data points on the right side of the plot are for ranking methods that have higher fail fractions at the decision point for the vehicles that are called in for the scrappage ASM test.

Therefore, the most desirable ranking methods are those that are in the lower right portion of the graph. There is a cluster of nine ranking methods with ΔFTP HC+NX/vehicle value equal to about -240 g/24 months/$ and a fail fraction of about 0.48. These ranking methods produce large decreases in ΔFTP HC+NX for every dollar spent on purchasing scrappage vehicles and about 48% of the vehicles that are called in for a scrappage ASM test would fail. All of these nine methods have vehicle value in the denominator and use RSD information for at least some of the inputs.

To the left of those nine data points is a cluster of six points for ranking methods that also have vehicle value in the denominator but do not use RSD information. These six ranking methods produce reductions in FTP HC+NX that are just as large as those produced by the methods that use RSD information. The only major difference between the two clusters is that the RSD-containing methods have fail fractions that are approximately 12% higher than those rankings methods that do not contain RSD information. For example, consider the two ranking methods FprobDP/$ by A (small red dot) and FprobDP/$ by F (small purple dot). Both have estimated FTP HC+NX changes of about -260 g/24 months/$ while FprobDP/$ by A has a fail fraction of about 32% and FprobDP/$ by F has a fail fraction of about 44%. FprobDP/$ by A uses only model year and estimated vehicle value to rank vehicles. FprobDP/$ by F uses only RSD HC, CO, and NX and estimated vehicle value to rank vehicles. Thus, the only substantial benefit of FprobDP/$ by F over FprobDP/$ by A is that the fail fraction at the Decision Point is about 12% higher. As we shall see in the implementation report, this increase in fail fraction is purchased by the operation of an RSD measurement program that can cover only a fraction of the fleet.

Figure 5-35. Comparison of FTP Reduction and ASM Fail Fraction for 27 Scrapping Ranking Methods



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5.5 Expected versus Modeled Strategy Performance

In all of the calculations in this report, we assumed that the participation of vehicles in the special strategies was 100%. This means that we assumed that all vehicles that were directed would go to the high-performing stations, that all vehicles that were exempted would not come in for their regular I/M inspections, that all vehicles that were called-in would actually come in for their call-in ASM off-cycle test and if they failed they would receive repairs and meet the follow-up ASM requirements, that all vehicles that were targeted for a scrappage ASM test would come in and receive the test and if they failed the scrappage ASM test, they would accept the scrappage offer and sell their vehicle to the State. To the extent that this 100% participation in the strategies would not be achieved, the benefits of the strategies would be reduced. This means that the real changes in failed miles driven, the real changes in FTP mass emissions, and the real fail rates at the Decision Point will be reduced relative to the values calculated in this report. Therefore, it also means that the incremental changes produced by the addition of RSD information to other information that is used to select vehicles for these strategies will be smaller than the estimates of the RSD influences that are reported here. Thus, the size of the RSD influences that are reported here are the largest that we expect they could ever be in a real situation where an RSD measurement component is added to the existing California I/M program.

We know, for example, that based on the experience of other jurisdictions that only a fraction of vehicles that are called in would actually show up. Accordingly, the benefits calculated for the Calling-In strategy would be substantially less than calculated in this report. Similarly, one could expect that only a fraction of vehicle owners would respond to a request to bring in their vehicle for a scrappage ASM test and only a portion of those who do come in would accept the scrappage offer. The state of California already has experience with a Directing program and, therefore, has an estimate of the level of success that can be achieved with that strategy. In the case of Exempting, since it requires little action on the part of the vehicle owner, we expect that this strategy could achieve near 100% participation.

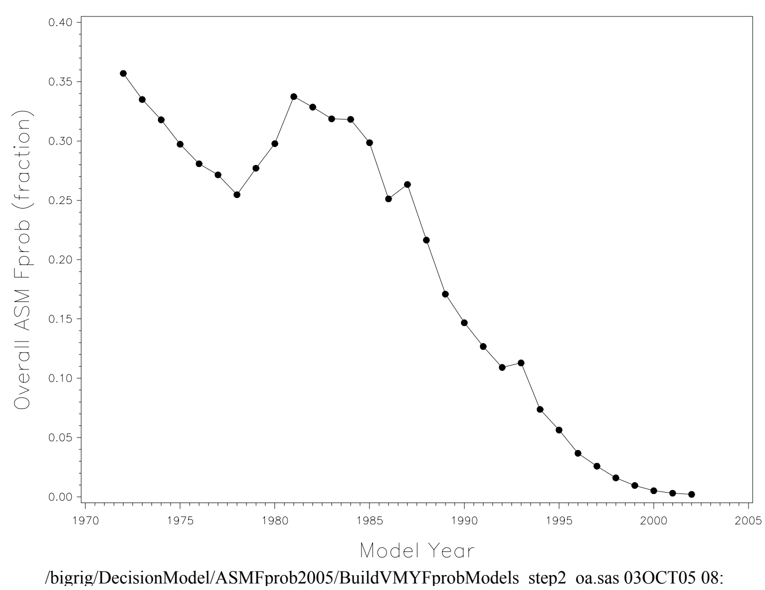
Appendix A

Model A for ASM Failure Probability

One of the simplest failure probability models that can be developed is one that is based only on the model year of the vehicle. While it is not likely that such a model would actually be used in the I/M program, this model serves as a standard of comparison for other more detailed models. All other models should be superior to this model in performance. Since a model-year model uses only the model year of a vehicle to look up the overall ASM Fprob, the model does not distinguish the effects of fuel metering, emission control system technology, ASM cutpoints, vehicle aging, previous I/M program inspection results, or time since previous-cycle I/M inspection. Because of this, Model A is not time dependent. The Fprob values calculated by Model A become obsolete as vehicles age. For example, the overall Fprob for a 2001 model year vehicle by Model A is 0.00314 based on VID data collected between 1998 and 2005. However, the actual overall Fprob for a 2001 vehicle will be substantially higher in calendar year 2010 because of vehicle aging.

Model A Fprob values were built on the same dataset that was used to build the other Fprob models in this project so that the Fprob values and the results of models could be compared on the same basis.[39] The resulting overall ASM Fprob by model year are plotted in Figure A-1. The Fprob values for 1972 and 1973 were calculated by extrapolation from the values for subsequent years since no observations for these model years were present in the VID.

Figure A-1. Model A Overall ASM Fprobs by Model Year



[39] Model A overall ASM Fprob values were calculated using the programs \bigrig\DecisionModel\ASMFprob2005\BuildVMYFprobModels_oa.sas and BuildVMYFprobModels_step2_oa.sas. The first program read in asmfprobmodelset_****.sas7bat for the 8 MET_ECS technologies. These datasets were created by MakeASMFprobModelSets.sas.

The dataset used to calculate the Model A overall ASM Fprobs included all observations where model year was determined by the VIN Decoder and where all six ASM mode/pollutant pass/fail results could be calculated. The observations also included all instances of inspections. That is, initial as well as subsequent inspections during each cycle were used. Also, all ASM inspections from June 1998 through April 2005 were used. Accordingly, the effects of vehicle aging were smeared in the dataset used to calculate these Model A Fprob values. Also during the period of the data used to develop the values, ASM cutpoints were periodically made more stringent. Because Model A does not include any cutpoint functionality, these changes in cutpoint cannot be included. Finally, since Model A does not include any cutpoint functionality, expected ASM mode/pollutant concentrations for individual vehicles cannot be calculated by integration from Model A. Because Model A Fprobs do not contain any time dependence, all forecasted Fprob values using Model A are constant.

The following Model A look-up table can be used to determine the overall ASM failure probability of a vehicle based on vehicle model year. These values cannot be used to estimate average ASM emissions or average FTP emissions.

Table A-1. Model A Overall ASM Failure Probabilities by Model Year

Model Year	Overall ASM Fprob
1972	0.35700
1973	0.33500
1974	0.31787
1975	0.29730
1976	0.28083
1977	0.27147
1978	0.25474
1979	0.27707
1980	0.29779
1981	0.33746
1982	0.32859
1983	0.31867
1984	0.31826
1985	0.29858
1986	0.25123
1987	0.26337
1988	0.21648
1989	0.17093
1990	0.14680
1991	0.12680
1992	0.10915
1993	0.11293
1994	0.07378
1995	0.05639
1996	0.03675
1997	0.02591
1998	0.01602
1999	0.00961
2000	0.00520
2001	0.00314
2002	0.00214

Appendix B

Model B ASM Failure Probability Equations

The following Model B equations can be used to calculate overall ASM failure probability of a vehicle based on vehicle description. These equations are simply a special case of the Model C equations where the VID history and ASM cutpoint terms have been dropped in Equations B-23 through 31. To serve as examples, the coefficients in Equations B-5, 6, and 7 are specific to engines described as FNTE / FORD_CAR / 3.0L_V6_N, and Equations B-23 through 31 are specific to engines described as FNTE / FORD_CAR / 3.0L_V6_N / 1988. Coefficients for most other combinations of Met_ECS / Make_CarTrk / Engine / Year are available. The equations cannot be used to estimate average ASM emissions or average FTP emissions.

$$F_{\text{Overall Model B}} = 1 - (P_{HC}) * (P_{CO} \mid \text{HC Pass}) * (P_{NX} \mid \text{HC,CO Pass}) \qquad \text{[B-1]}$$

where:

$$P_{HC} = \exp(\text{arg3\_HCunc}) / (1 + \exp(\text{arg3\_HCunc})) \qquad \text{[B-2]}$$

$$P_{CO} \mid \text{HC Pass} = \exp(\text{arg3\_COcon}) / (1 + \exp(\text{arg3\_COcon})) \qquad \text{[B-3]}$$

$$P_{NX} \mid \text{HC,CO Pass} = \exp(\text{arg3\_NXcon}) / (1 + \exp(\text{arg3\_NXcon})) \qquad \text{[B-4]}$$

where, for example,
Met_ECS = FNTE, Make_CarTrk = FORD_CAR, Engine = 3.0L_V6_N, all years:

$$\begin{aligned} \text{arg3\_HCunc} = \; & + 1.23201 \qquad \text{[B-5]} \\ & - 1.03501 * \text{logit\_}F_{HC} \\ & + 0.34276 * \text{logit\_}F_{CO} \\ & + 0.36198 * \text{logit\_}F_{NX} \\ & - 0.02365 * \text{logit\_}F_{HC} * \text{logit\_}F_{CO} \\ & + 0.00000 * \text{logit\_}F_{HC} * \text{logit\_}F_{NX} \\ & + 0.11182 * \text{logit\_}F_{CO} * \text{logit\_}F_{NX} \end{aligned}$$

$$\begin{aligned} \text{arg3\_COcon} = \; & + 5.1752 \qquad \text{[B-6]} \\ & + 0.37800 * \text{logit\_}F_{HC} \\ & - 0.82481 * \text{logit\_}F_{CO} \\ & + 0.74703 * \text{logit\_}F_{NX} \\ & + 0.00000 * \text{logit\_}F_{HC} * \text{logit\_}F_{CO} \\ & + 0.00000 * \text{logit\_}F_{HC} * \text{logit\_}F_{NX} \\ & + 0.11321 * \text{logit\_}F_{CO} * \text{logit\_}F_{NX} \end{aligned}$$

$$\begin{aligned} \text{arg3\_NXcon} = \; & + 1.56075 \qquad \text{[B-7]} \\ & - 0.10537 * \text{logit\_}F_{HC} \\ & + 0.18392 * \text{logit\_}F_{CO} \\ & - 0.42082 * \text{logit\_}F_{NX} \\ & - 0.11833 * \text{logit\_}F_{HC} * \text{logit\_}F_{CO} \\ & - 0.050429 * \text{logit\_}F_{HC} * \text{logit\_}F_{NX} \\ & + 0.23443 * \text{logit\_}F_{CO} * \text{logit\_}F_{NX} \end{aligned}$$

where:

$$logit\_F_{HC} = \ln(F_{HC} / (1-F_{HC})) \quad [B-8]$$

$$logit\_F_{CO} = \ln(F_{CO} / (1-F_{CO})) \quad [B-9]$$

$$logit\_F_{NX} = \ln(F_{NX} / (1-F_{NX})) \quad [B-10]$$

where:

$$F_{HC} = 1 - (P_{HC2}) * (P_{HC5} \mid \text{HC2 Pass}) \quad [B-11]$$

$$F_{CO} = 1 - (P_{CO2}) * (P_{CO5} \mid \text{CO2 Pass}) \quad [B-12]$$

$$F_{NX} = 1 - (P_{NX2}) * (P_{NX5} \mid \text{NX2 Pass}) \quad [B-13]$$

where:

$$P_{HC2} = \exp(arg2\_HC2unc) / (1 + \exp(arg2\_HC2unc)) \quad [B-14]$$

$$P_{HC5} = \exp(arg2\_HC5unc) / (1 + \exp(arg2\_HC5unc)) \quad [B-15]$$

$$P_{HC5} \mid \text{HC2 Pass} = \exp(arg2\_HC5con) / (1 + \exp(arg2\_HC5con)) \quad [B-16]$$

$$P_{CO2} = \exp(arg2\_CO2unc) / (1 + \exp(arg2\_CO2unc)) \quad [B-17]$$

$$P_{CO5} = \exp(arg2\_CO5unc) / (1 + \exp(arg2\_CO5unc)) \quad [B-18]$$

$$P_{CO5} \mid \text{CO2 Pass} = \exp(arg2\_CO5con) / (1 + \exp(arg2\_CO5con)) \quad [B-19]$$

$$P_{NX2} = \exp(arg2\_NX2unc) / (1 + \exp(arg2\_NX2unc)) \quad [B-20]$$

$$P_{NX5} = \exp(arg2\_NX5unc) / (1 + \exp(arg2\_NX5unc)) \quad [B-21]$$

$$P_{NX5} \mid \text{NX2 Pass} = \exp(arg2\_NX5con) / (1 + \exp(arg2\_NX5con)) \quad [B-22]$$

where, for example,
Met_ECS = FNTE, Make_CarTrk = FORD_CAR, Engine = 3.0L_V6_N, Year = 1988:

arg2_HC2_unc =	+ 2.1643	[B-23]
arg2_HC5_unc =	+ 2.2837	[B-24]
arg2_HC5_con =	+ 4.2424	[B-25]
arg2_CO2_unc =	+ 2.6290	[B-26]
arg2_CO5_unc =	+ 2.8404	[B-27]
arg2_CO5_con =	+ 4.4742	[B-28]
arg2_NX2_unc =	+ 3.0304	[B-29]
arg2_NX5_unc =	+ 2.7539	[B-30]
arg2_NX5_con =	+ 3.6745	[B-31]

where:

$P_{NX} \mid$ HC,CO Pass — denotes the fractional conditional Passing probability of ASM NX (that is, both ASM2525 NX and ASM5015 NX pass) given that ASM HC (both modes) and ASM CO (both modes) have already passed.

F_{HC} — denotes the fractional unconditional Failing probability of ASM HC (that is, either ASM2525 HC or ASM5015 HC fail or both).

$P_{NX5} \mid$ NX2 Pass — denotes the fractional conditional Passing probability of ASM5015 NX given that ASM2525 NX has already passed.

HC2	denotes ASM2525 HC
HC5	denotes ASM5015 HC
CO2	denotes ASM2525 CO
CO5	denotes ASM5015 CO
NX2	denotes ASM2525 NX
NX5	denotes ASM5015 NX

Appendix C

Model C ASM Failure Probability Equations

The following Model C equations can be used to calculate time-dependent overall ASM failure probability of a vehicle based on VID history and ASM cutpoints. To serve as examples, the coefficients in Equations C-5, 6, and 7 are specific to engines described as FNTE / FORD_CAR / 3.0L_V6_N and Equations C-23 through 31 are specific to engines described as FNTE / FORD_CAR / 3.0L_V6_N / 1988. Coefficients for most other combinations of Met_ECS / Make_CarTrk / Engine / Year are available. Equations C-14, 15, 17, 18, 20, and 21 can be used with calculus to estimate time-dependent average ASM emissions and with ASM-to-FTP relationships to estimate time-dependent average FTP emissions.

$$F_{\text{Overall Model C}} = 1 - (P_{HC}) * (P_{CO} \mid \text{HC Pass}) * (P_{NX} \mid \text{HC,CO Pass}) \qquad \text{[C-1]}$$

where:

$$P_{HC} = \exp(\text{arg3\_HCunc}) / (1 + \exp(\text{arg3\_HCunc})) \qquad \text{[C-2]}$$

$$P_{CO} \mid \text{HC Pass} = \exp(\text{arg3\_COcon}) / (1 + \exp(\text{arg3\_COcon})) \qquad \text{[C-3]}$$

$$P_{NX} \mid \text{HC,CO Pass} = \exp(\text{arg3\_NXcon}) / (1 + \exp(\text{arg3\_NXcon})) \qquad \text{[C-4]}$$

where, for example,
Met_ECS = FNTE, Make_CarTrk = FORD_CAR, Engine = 3.0L_V6_N, all years:

$$\begin{aligned} \text{arg3\_HCunc} = \; & + 1.23201 \qquad \text{[C-5]} \\ & - 1.03501 * \text{logit\_}F_{HC} \\ & + 0.34276 * \text{logit\_}F_{CO} \\ & + 0.36198 * \text{logit\_}F_{NX} \\ & - 0.02365 * \text{logit\_}F_{HC} * \text{logit\_}F_{CO} \\ & + 0.00000 * \text{logit\_}F_{HC} * \text{logit\_}F_{NX} \\ & + 0.11182 * \text{logit\_}F_{CO} * \text{logit\_}F_{NX} \end{aligned}$$

$$\begin{aligned} \text{arg3\_COcon} = \; & + 5.1752 \qquad \text{[C-6]} \\ & + 0.37800 * \text{logit\_}F_{HC} \\ & - 0.82481 * \text{logit\_}F_{CO} \\ & + 0.74703 * \text{logit\_}F_{NX} \\ & + 0.00000 * \text{logit\_}F_{HC} * \text{logit\_}F_{CO} \\ & + 0.00000 * \text{logit\_}F_{HC} * \text{logit\_}F_{NX} \\ & + 0.11321 * \text{logit\_}F_{CO} * \text{logit\_}F_{NX} \end{aligned}$$

$$\begin{aligned} \text{arg3\_NXcon} = \; & + 1.56075 \qquad \text{[C-7]} \\ & - 0.10537 * \text{logit\_}F_{HC} \\ & + 0.18392 * \text{logit\_}F_{CO} \\ & - 0.42082 * \text{logit\_}F_{NX} \\ & - 0.11833 * \text{logit\_}F_{HC} * \text{logit\_}F_{CO} \\ & - 0.050429 * \text{logit\_}F_{HC} * \text{logit\_}F_{NX} \\ & + 0.23443 * \text{logit\_}F_{CO} * \text{logit\_}F_{NX} \end{aligned}$$

where:

$$\text{logit\_}F_{HC} = \ln(F_{HC} / (1 - F_{HC})) \qquad [C\text{-}8]$$

$$\text{logit\_}F_{CO} = \ln(F_{CO} / (1 - F_{CO})) \qquad [C\text{-}9]$$

$$\text{logit\_}F_{NX} = \ln(F_{NX} / (1 - F_{NX})) \qquad [C\text{-}10]$$

where:

$$F_{HC} = 1 - (P_{HC2}) * (P_{HC5} \mid \text{HC2 Pass}) \qquad [C\text{-}11]$$

$$F_{CO} = 1 - (P_{CO2}) * (P_{CO5} \mid \text{CO2 Pass}) \qquad [C\text{-}12]$$

$$F_{NX} = 1 - (P_{NX2}) * (P_{NX5} \mid \text{NX2 Pass}) \qquad [C\text{-}13]$$

where:

$$P_{HC2} = \exp(\text{arg2\_HC2unc}) / (1 + \exp(\text{arg2\_HC2unc})) \qquad [C\text{-}14]$$

$$P_{HC5} = \exp(\text{arg2\_HC5unc}) / (1 + \exp(\text{arg2\_HC5unc})) \qquad [C\text{-}15]$$

$$P_{HC5} \mid \text{HC2 Pass} = \exp(\text{arg2\_HC5con}) / (1 + \exp(\text{arg2\_HC5con})) \qquad [C\text{-}16]$$

$$P_{CO2} = \exp(\text{arg2\_CO2unc}) / (1 + \exp(\text{arg2\_CO2unc})) \qquad [C\text{-}17]$$

$$P_{CO5} = \exp(\text{arg2\_CO5unc}) / (1 + \exp(\text{arg2\_CO5unc})) \qquad [C\text{-}18]$$

$$P_{CO5} \mid \text{CO2 Pass} = \exp(\text{arg2\_CO5con}) / (1 + \exp(\text{arg2\_CO5con})) \qquad [C\text{-}19]$$

$$P_{NX2} = \exp(\text{arg2\_NX2unc}) / (1 + \exp(\text{arg2\_NX2unc})) \qquad [C\text{-}20]$$

$$P_{NX5} = \exp(\text{arg2\_NX5unc}) / (1 + \exp(\text{arg2\_NX5unc})) \qquad [C\text{-}21]$$

$$P_{NX5} \mid \text{NX2 Pass} = \exp(\text{arg2\_NX5con}) / (1 + \exp(\text{arg2\_NX5con})) \qquad [C\text{-}22]$$

where, for example,
Met_ECS = FNTE, Make_CarTrk = FORD_CAR, Engine = 3.0L_V6_N, Year = 1988:

arg2_HC2_unc = [C-23]

```
        + 2.1643
        – 2.5337      *  (ln(ln(vehage)) – 0.97499)
        + 1.2435      *  (ln(ctpt_HC2) – 5.1400)
        + 0.048599    *  (previnit_asm_exist – 0.71055)
        – 0.16438     *  (previnit_tsi_exist – 0.24299)
        + 1.3865      *  (previnit_pass – 0.82698)   * previnit_asm_exist
        – 0.00072747  *  (dsp_asm – 608.20)          * previnit_asm_exist
        – 0.00091714  *  (dsp_tsi – 730.56)          * previnit_tsi_exist
```

arg2_HC5_unc = [C-24]

```
        + 2.2837
        – 2.6273      *  (ln(ln(vehage)) – 0.97499)
        + 1.5815      *  (ln(ctpt_HC5) – 5.3031)
        + 0.031655    *  (previnit_asm_exist – 0.71055)
        – 0.16810     *  (previnit_tsi_exist – 0.24299)
        + 1.2476      *  (previnit_pass – 0.84200)   * previnit_asm_exist
        – 0.00073301  *  (dsp_asm – 608.20)          * previnit_asm_exist
        – 0.00086360  *  (dsp_tsi – 730.55)          * previnit_tsi_exist
```

$$
\begin{aligned}
\text{arg2\_HC5\_con} = {} & \\
& + 4.2424 \\
& - 3.3854 && * \ (\ln(\ln(\text{vehage})) - 0.97491) \\
& + 1.1365 && * \ (\ln(\text{ctpt\_HC5}) - 5.3207) \\
& - 0.37525 && * \ (\text{previnit\_asm\_exist} - 0.71306) \\
& - 0.14486 && * \ (\text{previnit\_tsi\_exist} - 0.24084) \\
& + 1.2342 && * \ (\text{previnit\_pass} - 0.85278) && * \ \text{previnit\_asm\_exist} \\
& - 0.00065598 && * \ (\text{dsp\_asm} - 606.23) && * \ \text{previnit\_asm\_exist} \\
& + 0.00018816 && * \ (\text{dsp\_tsi} - 726.03) && * \ \text{previnit\_tsi\_exist}
\end{aligned}
\qquad [\text{C-25}]
$$

$$
\begin{aligned}
\text{arg2\_CO2\_unc} = {} & \\
& + 2.6290 \\
& - 2.8048 && * \ (\ln(\ln(\text{vehage})) - 0.97499) \\
& + 0.70466 && * \ (\ln(\text{ctpt\_CO2}) - 0.62834) \\
& + 0.14344 && * \ (\text{previnit\_asm\_exist} - 0.71055) \\
& - 0.0083643 && * \ (\text{previnit\_tsi\_exist} - 0.24299) \\
& + 1.0902 && * \ (\text{previnit\_pass} - 0.87617) && * \ \text{previnit\_asm\_exist} \\
& - 0.00068391 && * \ (\text{dsp\_asm} - 608.20) && * \ \text{previnit\_asm\_exist} \\
& - 0.0010395 && * \ (\text{dsp\_tsi} - 730.55) && * \ \text{previnit\_tsi\_exist}
\end{aligned}
\qquad [\text{C-26}]
$$

$$
\begin{aligned}
\text{arg2\_CO5\_unc} = {} & \\
& + 2.8404 \\
& - 2.9513 && * \ (\ln(\ln(\text{vehage})) - 0.97499) \\
& + 0.76808 && * \ (\ln(\text{ctpt\_CO5}) - 0.72026) \\
& + 0.16865 && * \ (\text{previnit\_asm\_exist} - 0.71055) \\
& - 0.0017439 && * \ (\text{previnit\_tsi\_exist} - 0.24299) \\
& + 1.0614 && * \ (\text{previnit\_pass} - 0.88623) && * \ \text{previnit\_asm\_exist} \\
& - 0.00082158 && * \ (\text{dsp\_asm} - 608.20) && * \ \text{previnit\_asm\_exist} \\
& - 0.00088322 && * \ (\text{dsp\_tsi} - 730.55) && * \ \text{previnit\_tsi\_exist}
\end{aligned}
\qquad [\text{C-27}]
$$

$$
\begin{aligned}
\text{arg2\_CO5\_con} = {} & \\
& + 4.4742 \\
& - 3.3284 && * \ (\ln(\ln(\text{vehage})) - 0.97485) \\
& + 0.43018 && * \ (\ln(\text{ctpt\_CO5}) - 0.74568) \\
& - 0.048911 && * \ (\text{previnit\_asm\_exist} - 0.71095) \\
& - 0.24150 && * \ (\text{previnit\_tsi\_exist} - 0.24324) \\
& + 1.0881 && * \ (\text{previnit\_pass} - 0.89105) && * \ \text{previnit\_asm\_exist} \\
& - 0.0010028 && * \ (\text{dsp\_asm} - 607.23) && * \ \text{previnit\_asm\_exist} \\
& - 0.00050519 && * \ (\text{dsp\_tsi} - 728.02) && * \ \text{previnit\_tsi\_exist}
\end{aligned}
\qquad [\text{C-28}]
$$

$$
\begin{aligned}
\text{arg2\_NX2\_unc} = {} & \\
& + 3.0304 \\
& - 1.1253 && * \ (\ln(\ln(\text{vehage})) - 0.97499) \\
& + 2.3692 && * \ (\ln(\text{ctpt\_NX2}) - 7.1270) \\
& + 0.35929 && * \ (\text{previnit\_asm\_exist} - 0.71055) \\
& + 0.21256 && * \ (\text{previnit\_tsi\_exist} - 0.24299)
\end{aligned}
\qquad [\text{C-29}]
$$

+ 1.6695 * (previnit_pass – 0.91041) * previnit_asm_exist
– 0.00087476 * (dsp_asm – 608.20) * previnit_asm_exist
– 0.00069790 * (dsp_tsi – 730.55) * previnit_tsi_exist

arg2_NX5_unc = [C-30]
+ 2.7539
– 1.5566 * (ln(ln(vehage)) – 0.97499)
+ 2.4525 * (ln(ctpt_NX5) – 7.2496)
+ 0.24983 * (previnit_asm_exist – 0.71055)
+ 0.13839 * (previnit_tsi_exist – 0.24299)
+ 1.5774 * (previnit_pass – 0.89248) * previnit_asm_exist
– 0.00096416 * (dsp_asm – 608.20) * previnit_asm_exist
– 0.00067473 * (dsp_tsi – 730.55) * previnit_tsi_exist

arg2_NX5_con = [C-31]
+ 3.6745
– 4.5356 * (ln(ln(vehage)) – 0.97405)
+ 2.4133 * (ln(ctpt_NX5) – 7.2627)
– 0.011876 * (previnit_asm_exist – 0.70404)
– 0.10894 * (previnit_tsi_exist – 0.24904)
+ 1.3972 * (previnit_pass – 0.90144) * previnit_asm_exist
– 0.00078213 * (dsp_asm – 604.91) * previnit_asm_exist
– 0.00088100 * (dsp_tsi – 729.82) * previnit_tsi_exist

where:

P_{NX} | HC,CO Pass	denotes the fractional conditional Passing probability of ASM NX (that is, both ASM2525 NX and ASM5015 NX pass) given that ASM HC (both modes) and ASM CO (both modes) have already passed.
F_{HC}	denotes the fractional unconditional Failing probability of ASM HC (that is, either ASM2525 HC or ASM5015 HC fail or both).
P_{NX5} | NX2 Pass	denotes the fractional conditional Passing probability of ASM5015 NX given that ASM2525 NX has already passed.
HC2	denotes ASM2525 HC
HC5	denotes ASM5015 HC
CO2	denotes ASM2525 CO
CO5	denotes ASM5015 CO
NX2	denotes ASM2525 NX
NX5	denotes ASM5015 NX
vehage	= vehicle age in years from January 1 of the vehicle model year.

ctpt_HC2	= ASM2525 HC cutpoint (ppm)
ctpt_HC5	= ASM5015 HC cutpoint (ppm)
ctpt_CO2	= ASM2525 CO cutpoint (%)
ctpt_CO5	= ASM5015 CO cutpoint (%)
ctpt_NX2	= ASM2525 NX cutpoint (ppm)
ctpt_NX5	= ASM5015 NX cutpoint (ppm)
previnit_asm_exist	= 1, if the vehicle has a previous-cycle ASM result of the same ASM mode/pollutant; = 0, if the vehicle does not have a previous-cycle ASM result of the same mode/pollutant.
previnit_tsi_exist	= 1, if the vehicle has a previous-cycle TSI emissions result; = 0, if the vehicle does not have a previous-cycle TSI emissions result.
previnit_pass	=1, if the previous-cycle initial-ASM emissions result of the same mode/pollutant is a pass; =0, if the previous-cycle initial-ASM emissions result of the same mode/pollutant is a fail that is ultimately followed in the same cycle by a pass with a certification.
dsp_asm	= number of days since the previous-cycle initial ASM if the previous-cycle initial-ASM emissions result of the same mode/pollutant is a pass; = number of days since the previous-cycle certified-passing ASM if the previous-cycle initial-ASM emissions result of the same mode/pollutant is a fail that is ultimately followed in the same cycle by a pass with a certification.
dsp_tsi	= number of days since the previous-cycle initial TSI if the previous-cycle initial emissions test is a TSI.

Table C-1. SAS Output for Equations C-14 and C-23

```
                                          HC-2-U                        10:20 Tuesday, July 19, 2005  49

----------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N -----------------------------------

                                         The LOGISTIC Procedure

                                           Model Information

                              Data Set                      WORK.CLEAN1
                              Response Variable             hc2passx
                              Number of Response Levels     2
                              Number of Observations        771670
                              Link Function                 Logit
                              Optimization Technique        Fisher's scoring


                                           Response Profile

                                    Ordered                      Total
                                      Value     hc2passx     Frequency

                                          1            1        747778
                                          2            0         23892

NOTE: 8281 observations were deleted due to missing values for the response or explanatory variables.


                                        Class Level Information

                                                    Design Variables

    Class    Value     1    2    3    4    5    6    7    8    9   10   11   12   13   14   15   16   17   18   19   20

    vMY      1986      1    0    0    0    0    0    0    0    0    0    0    0    0    0    0    0
             1987      0    1    0    0    0    0    0    0    0    0    0    0    0    0    0    0
             1988      0    0    1    0    0    0    0    0    0    0    0    0    0    0    0    0
             1989      0    0    0    1    0    0    0    0    0    0    0    0    0    0    0    0
             1990      0    0    0    0    1    0    0    0    0    0    0    0    0    0    0    0
             1991      0    0    0    0    0    1    0    0    0    0    0    0    0    0    0    0
             1992      0    0    0    0    0    0    1    0    0    0    0    0    0    0    0    0
             1993      0    0    0    0    0    0    0    1    0    0    0    0    0    0    0    0
             1994      0    0    0    0    0    0    0    0    1    0    0    0    0    0    0    0
             1995      0    0    0    0    0    0    0    0    0    1    0    0    0    0    0    0
             1996      0    0    0    0    0    0    0    0    0    0    1    0    0    0    0    0
             1997      0    0    0    0    0    0    0    0    0    0    0    1    0    0    0    0
             1999      0    0    0    0    0    0    0    0    0    0    0    0    1    0    0    0

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----------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N -----------------------------------

                                         The LOGISTIC Procedure

                                        Class Level Information

                                                    Design Variables

    Class    Value     1    2    3    4    5    6    7    8    9   10   11   12   13   14   15   16   17   18   19   20

             2000      0    0    0    0    0    0    0    0    0    0    0    0    0    1    0    0
             2001      0    0    0    0    0    0    0    0    0    0    0    0    0    0    1    0
             2002      0    0    0    0    0    0    0    0    0    0    0    0    0    0    0    1


                                        Model Convergence Status

                              Convergence criterion (GCONV=1E-8) satisfied.


                                         Model Fit Statistics

                                                Without          With
                                 Criterion     Covariates     Covariates

                                 AIC            1069761.8      171925.74
                                 SC             1069761.8      172214.65
                                 -2 Log L       1069761.8      171875.74


                                 Testing Global Null Hypothesis: BETA=0

                         Test                 Chi-Square       DF     Pr > ChiSq

                         Likelihood Ratio     897886.029       25         <.0001
                         Score                685123.316       25         <.0001
                         Wald                 180336.767       25         <.0001




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---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Type III Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > ChiSq
vMY	16	155468.433	<.0001
del_t_veh_age	1	282.1949	<.0001
del_lctpt	1	5803.6525	<.0001
del_previnit_pass	1	3930.4658	<.0001
del_dsp_asm_gt90only	1	266.4417	<.0001
del_previnit_asm_exi	1	2.5561	0.1099
LE_90d_since_asm	1	1411.3735	<.0001
del_previnit_tsi_exi	1	25.7392	<.0001
del_dsp_tsi_gt90only	1	88.9581	<.0001
LE_90d_since_tsi	1	3.8810	0.0488

Analysis of Maximum Likelihood Estimates

Parameter		DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
vMY	1986	1	2.5710	0.0267	9263.5284	<.0001
vMY	1987	1	1.8412	0.0154	14385.4092	<.0001
vMY	1988	1	2.1644	0.0159	18513.8139	<.0001
vMY	1989	1	3.1590	0.0215	21622.8162	<.0001
vMY	1990	1	3.2751	0.0207	25150.9171	<.0001
vMY	1991	1	3.8923	0.0284	18820.6499	<.0001
vMY	1992	1	4.2905	0.0320	18013.4681	<.0001
vMY	1993	1	3.8684	0.0315	15052.1814	<.0001
vMY	1994	1	4.7538	0.0426	12433.1731	<.0001
vMY	1995	1	4.1853	0.0272	23680.1636	<.0001
vMY	1996	1	5.2523	0.0348	22732.8014	<.0001
vMY	1997	1	6.0166	0.1777	1145.8271	<.0001
vMY	1999	1	7.0804	0.1400	2556.4516	<.0001
vMY	2000	1	7.8158	0.1980	1558.7037	<.0001
vMY	2001	1	8.3658	0.2568	1061.1763	<.0001
vMY	2002	1	9.4872	0.5815	266.2110	<.0001
del_t_veh_age		1	-2.5338	0.1508	282.1949	<.0001
del_lctpt		1	1.2436	0.0163	5803.6525	<.0001

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
del_previnit_pass	1	1.3866	0.0221	3930.4658	<.0001
del_dsp_asm_gt90only	1	-0.00073	0.000045	266.4417	<.0001
del_previnit_asm_exi	1	0.0486	0.0304	2.5561	0.1099
LE_90d_since_asm	1	1.8523	0.0493	1411.3735	<.0001
del_previnit_tsi_exi	1	-0.1644	0.0324	25.7392	<.0001
del_dsp_tsi_gt90only	1	-0.00092	0.000097	88.9581	<.0001
LE_90d_since_tsi	1	0.5876	0.2983	3.8810	0.0488

Odds Ratio Estimates

Effect		Point Estimate	95% Wald Confidence Limits	
vMY	1986 vs 2002	<0.001	<0.001	0.003
vMY	1987 vs 2002	<0.001	<0.001	0.001
vMY	1988 vs 2002	<0.001	<0.001	0.002
vMY	1989 vs 2002	0.002	<0.001	0.006
vMY	1990 vs 2002	0.002	<0.001	0.006
vMY	1991 vs 2002	0.004	0.001	0.012
vMY	1992 vs 2002	0.006	0.002	0.017
vMY	1993 vs 2002	0.004	0.001	0.011
vMY	1994 vs 2002	0.009	0.003	0.028
vMY	1995 vs 2002	0.005	0.002	0.016
vMY	1996 vs 2002	0.014	0.005	0.045
vMY	1997 vs 2002	0.031	0.009	0.102
vMY	1999 vs 2002	0.090	0.028	0.289
vMY	2000 vs 2002	0.188	0.057	0.623
vMY	2001 vs 2002	0.326	0.095	1.118
del_t_veh_age		0.079	0.059	0.107
del_lctpt		3.468	3.359	3.581
del_previnit_pass		4.001	3.831	4.178
del_dsp_asm_gt90only		0.999	0.999	0.999
del_previnit_asm_exi		1.050	0.989	1.114
LE_90d_since_asm		6.374	5.787	7.021

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
del_previnit_tsi_exi	0.848	0.796	0.904
del_dsp_tsi_gt90only	0.999	0.999	0.999
LE_90d_since_tsi	1.800	1.003	3.229

Association of Predicted Probabilities and Observed Responses

Percent Concordant	84.0	Somers' D	0.690
Percent Discordant	15.0	Gamma	0.697
Percent Tied	1.1	Tau-a	0.041
Pairs	17865911976	c	0.845

Partition for the Hosmer and Lemeshow Test

		hc2passx = 1		hc2passx = 0	
Group	Total	Observed	Expected	Observed	Expected
1	77104	65195	65219.25	11909	11884.75
2	77006	72212	72573.84	4794	4432.16
3	76954	74247	74287.69	2707	2666.31
4	77229	75503	75452.18	1726	1776.82
5	76983	75832	75736.24	1151	1246.76
6	78330	77547	77446.31	783	883.69
7	77598	77139	77021.87	459	576.13
8	77521	77267	77199.54	254	321.46
9	77620	77539	77501.41	81	118.59
10	75325	75297	75301.20	28	23.80

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
103.4972	8	<.0001

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Table C-2. SAS Output for Equations C-15 and C-24

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Model Information

Data Set	WORK.CLEAN1
Response Variable	hc5passx
Number of Response Levels	2
Number of Observations	771670
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	hc5passx	Total Frequency
1	1	750330
2	0	21340

NOTE: 8281 observations were deleted due to missing values for the response or explanatory variables.

Class Level Information

Design Variables

Class	Value	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
vMY	1986	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1987	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1988	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1989	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0				
	1990	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0				
	1991	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0				
	1992	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0				
	1993	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0				
	1994	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0				
	1995	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0				
	1996	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0				
	1997	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0				
	1999	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0				

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---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Class Level Information

Design Variables

Class	Value	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	2000	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0				
	2001	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0				
	2002	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1				

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Without Covariates	With Covariates
AIC	1069761.8	154530.39
SC	1069761.8	154819.29
-2 Log L	1069761.8	154480.39

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	915281.384	25	<.0001
Score	693953.245	25	<.0001
Wald	164005.874	25	<.0001

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---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Type III Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > ChiSq
vMY	16	139794.250	<.0001
del_t_veh_age	1	218.9072	<.0001
del_lctpt	1	5013.6994	<.0001
del_previnit_pass	1	2727.9521	<.0001
del_dsp_asm_gt90only	1	248.4338	<.0001
del_previnit_asm_exi	1	0.8951	0.3441
LE_90d_since_asm	1	1235.4811	<.0001
del_previnit_tsi_exi	1	21.9268	<.0001
del_dsp_tsi_gt90only	1	67.0041	<.0001
LE_90d_since_tsi	1	1.2537	0.2628

Analysis of Maximum Likelihood Estimates

Parameter		DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
vMY	1986	1	2.6062	0.0271	9217.2745	<.0001
vMY	1987	1	1.9031	0.0157	14730.4885	<.0001
vMY	1988	1	2.2837	0.0166	18853.7973	<.0001
vMY	1989	1	3.1233	0.0212	21642.7638	<.0001
vMY	1990	1	3.2438	0.0204	25198.0014	<.0001
vMY	1991	1	3.9332	0.0289	18501.5765	<.0001
vMY	1992	1	4.4127	0.0339	16986.9590	<.0001
vMY	1993	1	4.2502	0.0376	12761.6197	<.0001
vMY	1994	1	5.4142	0.0586	8538.7097	<.0001
vMY	1995	1	5.1272	0.0424	14651.5173	<.0001
vMY	1996	1	5.5080	0.0384	20603.6515	<.0001
vMY	1997	1	6.0259	0.1703	1251.3139	<.0001
vMY	1999	1	7.5242	0.1669	2033.4723	<.0001
vMY	2000	1	8.2353	0.2378	1199.2468	<.0001
vMY	2001	1	8.8878	0.3238	753.5858	<.0001
vMY	2002	1	17.8681	37.3082	0.2294	0.6320
del_t_veh_age		1	-2.6273	0.1776	218.9072	<.0001
del_lctpt		1	1.5815	0.0223	5013.6994	<.0001

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
del_previnit_pass	1	1.2477	0.0239	2727.9521	<.0001
del_dsp_asm_gt90only	1	-0.00073	0.000047	248.4338	<.0001
del_previnit_asm_exi	1	0.0317	0.0335	0.8951	0.3441
LE_90d_since_asm	1	1.9893	0.0566	1235.4811	<.0001
del_previnit_tsi_exi	1	-0.1681	0.0359	21.9268	<.0001
del_dsp_tsi_gt90only	1	-0.00086	0.000106	67.0041	<.0001
LE_90d_since_tsi	1	0.3228	0.2883	1.2537	0.2628

Odds Ratio Estimates

Effect		Point Estimate	95% Wald Confidence Limits	
vMY	1986 vs 2002	<0.001	<0.001	>999.999
vMY	1987 vs 2002	<0.001	<0.001	>999.999
vMY	1988 vs 2002	<0.001	<0.001	>999.999
vMY	1989 vs 2002	<0.001	<0.001	>999.999
vMY	1990 vs 2002	<0.001	<0.001	>999.999
vMY	1991 vs 2002	<0.001	<0.001	>999.999
vMY	1992 vs 2002	<0.001	<0.001	>999.999
vMY	1993 vs 2002	<0.001	<0.001	>999.999
vMY	1994 vs 2002	<0.001	<0.001	>999.999
vMY	1995 vs 2002	<0.001	<0.001	>999.999
vMY	1996 vs 2002	<0.001	<0.001	>999.999
vMY	1997 vs 2002	<0.001	<0.001	>999.999
vMY	1999 vs 2002	<0.001	<0.001	>999.999
vMY	2000 vs 2002	<0.001	<0.001	>999.999
vMY	2001 vs 2002	<0.001	<0.001	>999.999
del_t_veh_age		0.072	0.051	0.102
del_lctpt		4.862	4.654	5.080
del_previnit_pass		3.482	3.323	3.649
del_dsp_asm_gt90only		0.999	0.999	0.999
del_previnit_asm_exi		1.032	0.967	1.102
LE_90d_since_asm		7.310	6.543	8.168

----------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N -----------------------------------

The LOGISTIC Procedure

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
del_previnit_tsi_exi	0.845	0.788	0.907
del_dsp_tsi_gt90only	0.999	0.999	0.999
LE_90d_since_tsi	1.381	0.785	2.430

Association of Predicted Probabilities and Observed Responses

Percent Concordant	85.3	Somers' D	0.718
Percent Discordant	13.6	Gamma	0.725
Percent Tied	1.1	Tau-a	0.039
Pairs	16012042200	c	0.859

Partition for the Hosmer and Lemeshow Test

		hc5passx = 1		hc5passx = 0	
Group	Total	Observed	Expected	Observed	Expected
1	77134	65993	65979.23	11141	11154.77
2	77288	72829	73020.54	4459	4267.46
3	77356	74969	75019.72	2387	2336.28
4	76991	75613	75605.83	1378	1385.17
5	76988	76109	76065.84	879	922.16
6	76716	76147	76098.82	569	617.18
7	75336	75025	74953.68	311	382.32
8	78184	78036	77964.01	148	219.99
9	73880	73834	73804.74	46	75.26
10	81797	81775	81778.48	22	18.52

----------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N -----------------------------------

The LOGISTIC Procedure

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
65.1718	8	<.0001

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Table C-3. SAS Output for Equations C-16 and C-25

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---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Model Information

Data Set	WORK.CLEAN1
Response Variable	hc5passx
Number of Response Levels	2
Number of Observations	747778
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	hc5passx	Total Frequency
1	1	744112
2	0	3666

NOTE: 8279 observations were deleted due to missing values for the response or explanatory variables.

Class Level Information

Design Variables

Class	Value	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
vMY	1986	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1987	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1988	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1989	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0				
	1990	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0				
	1991	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0				
	1992	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0				
	1993	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0				
	1994	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0				
	1995	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0				
	1996	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0				
	1997	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0				
	1999	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0				

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---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Class Level Information

Design Variables

Class	Value	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	2000	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0				
	2001	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0				
	2002	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1				

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Without Covariates	With Covariates
AIC	1036640.4	40014.756
SC	1036640.4	40302.878
-2 Log L	1036640.4	39964.756

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	996675.669	25	<.0001
Score	733326.007	25	<.0001
Wald	75428.2336	25	<.0001

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---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Type III Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > ChiSq
vMY	16	59705.6991	<.0001
del_t_veh_age	1	66.8605	<.0001
del_lctpt	1	532.1308	<.0001
del_previnit_pass	1	580.3663	<.0001
del_dsp_asm_gt90only	1	41.7133	<.0001
del_previnit_asm_exi	1	17.8980	<.0001
LE_90d_since_asm	1	189.0247	<.0001
del_previnit_tsi_exi	1	2.2251	0.1358
del_dsp_tsi_gt90only	1	0.4698	0.4931
LE_90d_since_tsi	1	0.2411	0.6234

Analysis of Maximum Likelihood Estimates

Parameter		DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
vMY	1986	1	4.3695	0.0632	4782.6997	<.0001
vMY	1987	1	3.9974	0.0408	9576.9666	<.0001
vMY	1988	1	4.2425	0.0418	10307.4079	<.0001
vMY	1989	1	4.5588	0.0431	11208.3999	<.0001
vMY	1990	1	4.7065	0.0421	12508.5588	<.0001
vMY	1991	1	5.5583	0.0652	7265.7440	<.0001
vMY	1992	1	5.6541	0.0638	7851.5857	<.0001
vMY	1993	1	6.1897	0.0995	3868.8441	<.0001
vMY	1994	1	7.4915	0.1673	2004.3034	<.0001
vMY	1995	1	9.5093	0.3783	631.7580	<.0001
vMY	1996	1	6.5548	0.0689	9041.8366	<.0001
vMY	1997	1	7.0856	0.2917	589.9401	<.0001
vMY	1999	1	9.1777	0.3663	627.5951	<.0001
vMY	2000	1	11.1874	1.0030	124.4193	<.0001
vMY	2001	1	21.0574	123.1	0.0293	0.8641
vMY	2002	1	21.1558	163.4	0.0168	0.8970
del_t_veh_age		1	-3.3854	0.4140	66.8605	<.0001
del_lctpt		1	1.1366	0.0493	532.1308	<.0001

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
del_previnit_pass	1	1.2343	0.0512	580.3663	<.0001
del_dsp_asm_gt90only	1	-0.00066	0.000102	41.7133	<.0001
del_previnit_asm_exi	1	-0.3753	0.0887	17.8980	<.0001
LE_90d_since_asm	1	1.4609	0.1063	189.0247	<.0001
del_previnit_tsi_exi	1	-0.1449	0.0971	2.2251	0.1358
del_dsp_tsi_gt90only	1	0.000188	0.000275	0.4698	0.4931
LE_90d_since_tsi	1	-0.2864	0.5832	0.2411	0.6234

Odds Ratio Estimates

Effect		Point Estimate	95% Wald Confidence Limits	
vMY	1986 vs 2002	<0.001	<0.001	>999.999
vMY	1987 vs 2002	<0.001	<0.001	>999.999
vMY	1988 vs 2002	<0.001	<0.001	>999.999
vMY	1989 vs 2002	<0.001	<0.001	>999.999
vMY	1990 vs 2002	<0.001	<0.001	>999.999
vMY	1991 vs 2002	<0.001	<0.001	>999.999
vMY	1992 vs 2002	<0.001	<0.001	>999.999
vMY	1993 vs 2002	<0.001	<0.001	>999.999
vMY	1994 vs 2002	<0.001	<0.001	>999.999
vMY	1995 vs 2002	<0.001	<0.001	>999.999
vMY	1996 vs 2002	<0.001	<0.001	>999.999
vMY	1997 vs 2002	<0.001	<0.001	>999.999
vMY	1999 vs 2002	<0.001	<0.001	>999.999
vMY	2000 vs 2002	<0.001	<0.001	>999.999
vMY	2001 vs 2002	0.906	<0.001	>999.999
del_t_veh_age		0.034	0.015	0.076
del_lctpt		3.116	2.829	3.432
del_previnit_pass		3.436	3.108	3.799
del_dsp_asm_gt90only		0.999	0.999	1.000
del_previnit_asm_exi		0.687	0.577	0.818
LE_90d_since_asm		4.310	3.499	5.307

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
del_previnit_tsi_exi	0.865	0.715	1.047
del_dsp_tsi_gt90only	1.000	1.000	1.001
LE_90d_since_tsi	0.751	0.239	2.355

Association of Predicted Probabilities and Observed Responses

Percent Concordant	80.3	Somers' D	0.667
Percent Discordant	13.7	Gamma	0.709
Percent Tied	6.0	Tau-a	0.007
Pairs	2727914592	c	0.833

Partition for the Hosmer and Lemeshow Test

		hc5passx = 1		hc5passx = 0	
Group	Total	Observed	Expected	Observed	Expected
1	74814	73111	73067.82	1703	1746.18
2	75427	74620	74655.87	807	771.13
3	75898	75381	75420.18	517	477.82
4	76365	76062	76056.75	303	308.25
5	78045	77848	77838.35	197	206.65
6	76702	76618	76583.54	84	118.46
7	72066	72030	72019.39	36	46.61
8	66249	66235	66232.79	14	16.21
9	89024	89019	89014.00	5	10.00
10	63188	63188	63181.68	0	6.32

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
28.1305	8	0.0005

NOTE: In calculating the Expected values, predicted probabilities less than 0.0001 and greater than 0.9999 were changed to 0.0001 and 0.9999 respectively.

Table C-4. SAS Output for Equations C-17 and C-26

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Model Information

Data Set	WORK.CLEAN1
Response Variable	co2passx
Number of Response Levels	2
Number of Observations	771670
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	co2passx	Total Frequency
1	1	757943
2	0	13727

NOTE: 8281 observations were deleted due to missing values for the response or explanatory variables.

Class Level Information

Design Variables

Class	Value	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
vMY	1986	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1987	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1988	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1989	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0				
	1990	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0				
	1991	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0				
	1992	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0				
	1993	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0				
	1994	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0				
	1995	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0				
	1996	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0				
	1997	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0				
	1999	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0				

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Class Level Information

Design Variables

Class	Value	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	2000	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0				
	2001	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0				
	2002	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1				

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Without Covariates	With Covariates
AIC	1069761.8	106216.51
SC	1069761.8	106505.41
-2 Log L	1069761.8	106166.51

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	963595.263	25	<.0001
Score	720774.130	25	<.0001
Wald	126752.237	25	<.0001

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Type III Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > ChiSq
vMY	16	110758.934	<.0001
del_t_veh_age	1	158.0268	<.0001
del_lctpt	1	3183.4772	<.0001
del_previnit_pass	1	1207.9087	<.0001
del_dsp_asm_gt90only	1	138.1201	<.0001
del_previnit_asm_exi	1	12.9604	0.0003
LE_90d_since_asm	1	703.9907	<.0001
del_previnit_tsi_exi	1	0.0403	0.8410
del_dsp_tsi_gt90only	1	67.5956	<.0001
LE_90d_since_tsi	1	0.7433	0.3886

Analysis of Maximum Likelihood Estimates

Parameter		DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
vMY	1986	1	2.7287	0.0287	9068.6416	<.0001
vMY	1987	1	2.1503	0.0172	15710.9090	<.0001
vMY	1988	1	2.6290	0.0191	18971.0638	<.0001
vMY	1989	1	3.8905	0.0301	16692.6015	<.0001
vMY	1990	1	3.8758	0.0274	20076.5907	<.0001
vMY	1991	1	4.5366	0.0388	13666.7818	<.0001
vMY	1992	1	5.3497	0.0538	9891.1165	<.0001
vMY	1993	1	5.2087	0.0610	7300.9194	<.0001
vMY	1994	1	6.5392	0.1046	3909.9402	<.0001
vMY	1995	1	6.0546	0.0681	7906.3772	<.0001
vMY	1996	1	5.9568	0.0511	13570.5957	<.0001
vMY	1997	1	6.6391	0.2588	657.9122	<.0001
vMY	1999	1	8.7869	0.3367	681.1597	<.0001
vMY	2000	1	8.7357	0.3187	751.1124	<.0001
vMY	2001	1	10.1003	0.5841	298.9975	<.0001
vMY	2002	1	19.0045	63.5678	0.0894	0.7650
del_t_veh_age		1	-2.8049	0.2231	158.0268	<.0001
del_lctpt		1	0.7047	0.0125	3183.4772	<.0001

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
del_previnit_pass	1	1.0902	0.0314	1207.9087	<.0001
del_dsp_asm_gt90only	1	-0.00068	0.000058	138.1201	<.0001
del_previnit_asm_exi	1	0.1434	0.0398	12.9604	0.0003
LE_90d_since_asm	1	1.5951	0.0601	703.9907	<.0001
del_previnit_tsi_exi	1	-0.00836	0.0417	0.0403	0.8410
del_dsp_tsi_gt90only	1	-0.00104	0.000126	67.5956	<.0001
LE_90d_since_tsi	1	0.3149	0.3653	0.7433	0.3886

Odds Ratio Estimates

Effect		Point Estimate	95% Wald Confidence Limits	
vMY	1986 vs 2002	<0.001	<0.001	>999.999
vMY	1987 vs 2002	<0.001	<0.001	>999.999
vMY	1988 vs 2002	<0.001	<0.001	>999.999
vMY	1989 vs 2002	<0.001	<0.001	>999.999
vMY	1990 vs 2002	<0.001	<0.001	>999.999
vMY	1991 vs 2002	<0.001	<0.001	>999.999
vMY	1992 vs 2002	<0.001	<0.001	>999.999
vMY	1993 vs 2002	<0.001	<0.001	>999.999
vMY	1994 vs 2002	<0.001	<0.001	>999.999
vMY	1995 vs 2002	<0.001	<0.001	>999.999
vMY	1996 vs 2002	<0.001	<0.001	>999.999
vMY	1997 vs 2002	<0.001	<0.001	>999.999
vMY	1999 vs 2002	<0.001	<0.001	>999.999
vMY	2000 vs 2002	<0.001	<0.001	>999.999
vMY	2001 vs 2002	<0.001	<0.001	>999.999
del_t_veh_age		0.061	0.039	0.094
del_lctpt		2.023	1.974	2.073
del_previnit_pass		2.975	2.798	3.164
del_dsp_asm_gt90only		0.999	0.999	0.999
del_previnit_asm_exi		1.154	1.068	1.248
LE_90d_since_asm		4.929	4.381	5.545

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
del_previnit_tsi_exi	0.992	0.914	1.076
del_dsp_tsi_gt90only	0.999	0.999	0.999
LE_90d_since_tsi	1.370	0.670	2.803

Association of Predicted Probabilities and Observed Responses

Percent Concordant	87.4	Somers' D	0.764
Percent Discordant	11.0	Gamma	0.776
Percent Tied	1.6	Tau-a	0.027
Pairs	10404283561	c	0.882

Partition for the Hosmer and Lemeshow Test

		co2passx = 1		co2passx = 0	
Group	Total	Observed	Expected	Observed	Expected
1	77265	68907	68974.35	8358	8290.65
2	77154	74407	74543.36	2747	2610.64
3	76920	75768	75705.99	1152	1214.01
4	76701	76132	76053.88	569	647.12
5	77779	77407	77371.04	372	407.96
6	76791	76519	76527.70	272	263.30
7	78563	78413	78386.17	150	176.83
8	81346	81276	81237.90	70	108.10
9	88408	88374	88366.30	34	41.70
10	60743	60740	60736.93	3	6.07

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---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
44.6925	8	<.0001

NOTE: In calculating the Expected values, predicted probabilities less than 0.0001 and greater than 0.9999 were changed to 0.0001 and 0.9999 respectively.

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Table C-5. SAS Output for Equations C-18 and C-27

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Model Information

Data Set	WORK.CLEAN1
Response Variable	co5passx
Number of Response Levels	2
Number of Observations	771670
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	co5passx	Total Frequency
1	1	758744
2	0	12926

NOTE: 8281 observations were deleted due to missing values for the response or explanatory variables.

Class Level Information

Design Variables

Class	Value	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
vMY	1986	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1987	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1988	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1989	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0				
	1990	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0				
	1991	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0				
	1992	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0				
	1993	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0				
	1994	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0				
	1995	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0				
	1996	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0				
	1997	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0				
	1999	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0				

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Class Level Information

Design Variables

Class	Value	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	2000	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0				
	2001	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0				
	2002	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1				

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Without Covariates	With Covariates
AIC	1069761.8	100992.34
SC	1069761.8	101281.25
-2 Log L	1069761.8	100942.34

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	968819.430	25	<.0001
Score	723599.444	25	<.0001
Wald	122271.496	25	<.0001

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---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Type III Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > ChiSq
vMY	16	106239.374	<.0001
del_t_veh_age	1	163.9705	<.0001
del_lctpt	1	2986.6866	<.0001
del_previnit_pass	1	1048.5442	<.0001
del_dsp_asm_gt90only	1	184.3696	<.0001
del_previnit_asm_exi	1	17.1381	<.0001
LE_90d_since_asm	1	674.4163	<.0001
del_previnit_tsi_exi	1	0.0017	0.9673
del_dsp_tsi_gt90only	1	47.1691	<.0001
LE_90d_since_tsi	1	0.0617	0.8038

Analysis of Maximum Likelihood Estimates

Parameter		DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
vMY	1986	1	2.7729	0.0292	9014.8356	<.0001
vMY	1987	1	2.1444	0.0172	15607.7650	<.0001
vMY	1988	1	2.8404	0.0208	18694.8690	<.0001
vMY	1989	1	3.8596	0.0297	16871.6617	<.0001
vMY	1990	1	3.8451	0.0270	20282.8745	<.0001
vMY	1991	1	4.6269	0.0405	13056.9429	<.0001
vMY	1992	1	5.8627	0.0691	7201.4761	<.0001
vMY	1993	1	5.3375	0.0648	6779.1057	<.0001
vMY	1994	1	6.4024	0.0975	4312.2253	<.0001
vMY	1995	1	6.4199	0.0813	6231.9444	<.0001
vMY	1996	1	5.9309	0.0505	13810.9569	<.0001
vMY	1997	1	6.6482	0.2589	659.4841	<.0001
vMY	1999	1	8.5313	0.2929	848.5247	<.0001
vMY	2000	1	8.8687	0.3359	696.9123	<.0001
vMY	2001	1	10.5662	0.7132	219.5123	<.0001
vMY	2002	1	19.0639	63.1668	0.0911	0.7628
del_t_veh_age		1	-2.9513	0.2305	163.9705	<.0001
del_lctpt		1	0.7681	0.0141	2986.6866	<.0001

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---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
del_previnit_pass	1	1.0614	0.0328	1048.5442	<.0001
del_dsp_asm_gt90only	1	-0.00082	0.000061	184.3696	<.0001
del_previnit_asm_exi	1	0.1687	0.0407	17.1381	<.0001
LE_90d_since_asm	1	1.6949	0.0653	674.4163	<.0001
del_previnit_tsi_exi	1	-0.00174	0.0426	0.0017	0.9673
del_dsp_tsi_gt90only	1	-0.00088	0.000129	47.1691	<.0001
LE_90d_since_tsi	1	-0.0783	0.3153	0.0617	0.8038

Odds Ratio Estimates

Effect		Point Estimate	95% Wald Confidence Limits	
vMY	1986 vs 2002	<0.001	<0.001	>999.999
vMY	1987 vs 2002	<0.001	<0.001	>999.999
vMY	1988 vs 2002	<0.001	<0.001	>999.999
vMY	1989 vs 2002	<0.001	<0.001	>999.999
vMY	1990 vs 2002	<0.001	<0.001	>999.999
vMY	1991 vs 2002	<0.001	<0.001	>999.999
vMY	1992 vs 2002	<0.001	<0.001	>999.999
vMY	1993 vs 2002	<0.001	<0.001	>999.999
vMY	1994 vs 2002	<0.001	<0.001	>999.999
vMY	1995 vs 2002	<0.001	<0.001	>999.999
vMY	1996 vs 2002	<0.001	<0.001	>999.999
vMY	1997 vs 2002	<0.001	<0.001	>999.999
vMY	1999 vs 2002	<0.001	<0.001	>999.999
vMY	2000 vs 2002	<0.001	<0.001	>999.999
vMY	2001 vs 2002	<0.001	<0.001	>999.999
del_t_veh_age		0.052	0.033	0.082
del_lctpt		2.156	2.097	2.216
del_previnit_pass		2.891	2.711	3.082
del_dsp_asm_gt90only		0.999	0.999	0.999
del_previnit_asm_exi		1.184	1.093	1.282
LE_90d_since_asm		5.446	4.792	6.189

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---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
del_previnit_tsi_exi	0.998	0.918	1.085
del_dsp_tsi_gt90only	0.999	0.999	0.999
LE_90d_since_tsi	0.925	0.498	1.715

Association of Predicted Probabilities and Observed Responses

Percent Concordant	87.5	Somers' D	0.767
Percent Discordant	10.7	Gamma	0.781
Percent Tied	1.8	Tau-a	0.025
Pairs	9807524944	c	0.884

Partition for the Hosmer and Lemeshow Test

		co5passx = 1		co5passx = 0	
Group	Total	Observed	Expected	Observed	Expected
1	77214	69283	69391.01	7931	7822.99
2	76976	74369	74452.73	2607	2523.27
3	77220	76129	76044.73	1091	1175.27
4	77807	77322	77226.13	485	580.87
5	79319	78974	78969.16	345	349.84
6	79792	79558	79561.07	234	230.93
7	74824	74697	74681.04	127	142.96
8	78348	78283	78255.83	65	92.17
9	73032	72997	72993.93	35	38.07
10	77138	77132	77128.87	6	9.13

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---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
37.8446	8	<.0001

Table C-6. SAS Output for Equations C-19 and C-28

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Model Information

Data Set	WORK.CLEAN1
Response Variable	co5passx
Number of Response Levels	2
Number of Observations	757943
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	co5passx	Total Frequency
1	1	755244
2	0	2699

NOTE: 8281 observations were deleted due to missing values for the response or explanatory variables.

Class Level Information

Design Variables

Class	Value	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
vMY	1986	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1987	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1988	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1989	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0				
	1990	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0				
	1991	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0				
	1992	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0				
	1993	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0				
	1994	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0				
	1995	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0				
	1996	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0				
	1997	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0				
	1999	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0				

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Class Level Information

Design Variables

Class	Value	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	2000	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0				
	2001	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0				
	2002	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1				

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Without Covariates	With Covariates
AIC	1050732.1	31268.133
SC	1050732.1	31556.592
-2 Log L	1050732.1	31218.133

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	1019513.97	25	<.0001
Score	747269.584	25	<.0001
Wald	64150.4958	25	<.0001

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Type III Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > ChiSq
vMY	16	55449.0778	<.0001
del_t_veh_age	1	61.5732	<.0001
del_lctpt	1	241.4819	<.0001
del_previnit_pass	1	247.1696	<.0001
del_dsp_asm_gt90only	1	60.5075	<.0001
del_previnit_asm_exi	1	0.2869	0.5922
LE_90d_since_asm	1	96.9826	<.0001
del_previnit_tsi_exi	1	6.3760	0.0116
del_dsp_tsi_gt90only	1	3.4668	0.0626
LE_90d_since_tsi	1	0.2413	0.6233

Analysis of Maximum Likelihood Estimates

Parameter		DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
vMY	1986	1	4.3523	0.0638	4655.5372	<.0001
vMY	1987	1	3.9686	0.0404	9657.3763	<.0001
vMY	1988	1	4.4743	0.0466	9236.1734	<.0001
vMY	1989	1	5.0883	0.0562	8205.0505	<.0001
vMY	1990	1	5.1545	0.0530	9475.2185	<.0001
vMY	1991	1	6.0621	0.0857	5009.0380	<.0001
vMY	1992	1	6.6405	0.1064	3892.8516	<.0001
vMY	1993	1	6.6139	0.1275	2692.5081	<.0001
vMY	1994	1	7.2915	0.1586	2114.7021	<.0001
vMY	1995	1	8.2779	0.2137	1501.1127	<.0001
vMY	1996	1	6.4507	0.0695	8607.6289	<.0001
vMY	1997	1	9.3038	1.0005	86.4756	<.0001
vMY	1999	1	9.6399	0.5088	358.9942	<.0001
vMY	2000	1	21.6017	195.7	0.0122	0.9121
vMY	2001	1	22.0336	211.0	0.0109	0.9168
vMY	2002	1	22.1650	281.8	0.0062	0.9373
del_t_veh_age		1	-3.3285	0.4242	61.5732	<.0001
del_lctpt		1	0.4302	0.0277	241.4819	<.0001

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
del_previnit_pass	1	1.0881	0.0692	247.1696	<.0001
del_dsp_asm_gt90only	1	-0.00100	0.000129	60.5075	<.0001
del_previnit_asm_exi	1	-0.0489	0.0913	0.2869	0.5922
LE_90d_since_asm	1	1.1555	0.1173	96.9826	<.0001
del_previnit_tsi_exi	1	-0.2415	0.0956	6.3760	0.0116
del_dsp_tsi_gt90only	1	-0.00051	0.000271	3.4668	0.0626
LE_90d_since_tsi	1	-0.2866	0.5834	0.2413	0.6233

Odds Ratio Estimates

Effect		Point Estimate	95% Wald Confidence Limits	
vMY	1986 vs 2002	<0.001	<0.001	>999.999
vMY	1987 vs 2002	<0.001	<0.001	>999.999
vMY	1988 vs 2002	<0.001	<0.001	>999.999
vMY	1989 vs 2002	<0.001	<0.001	>999.999
vMY	1990 vs 2002	<0.001	<0.001	>999.999
vMY	1991 vs 2002	<0.001	<0.001	>999.999
vMY	1992 vs 2002	<0.001	<0.001	>999.999
vMY	1993 vs 2002	<0.001	<0.001	>999.999
vMY	1994 vs 2002	<0.001	<0.001	>999.999
vMY	1995 vs 2002	<0.001	<0.001	>999.999
vMY	1996 vs 2002	<0.001	<0.001	>999.999
vMY	1997 vs 2002	<0.001	<0.001	>999.999
vMY	1999 vs 2002	<0.001	<0.001	>999.999
vMY	2000 vs 2002	0.569	<0.001	>999.999
vMY	2001 vs 2002	0.877	<0.001	>999.999
del_t_veh_age		0.036	0.016	0.082
del_lctpt		1.538	1.456	1.623
del_previnit_pass		2.969	2.592	3.400
del_dsp_asm_gt90only		0.999	0.999	0.999
del_previnit_asm_exi		0.952	0.796	1.139
LE_90d_since_asm		3.176	2.523	3.997

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
del_previnit_tsi_exi	0.785	0.651	0.947
del_dsp_tsi_gt90only	0.999	0.999	1.000
LE_90d_since_tsi	0.751	0.239	2.356

Association of Predicted Probabilities and Observed Responses

Percent Concordant	77.2	Somers' D	0.644
Percent Discordant	12.8	Gamma	0.716
Percent Tied	10.0	Tau-a	0.005
Pairs	2038403556	c	0.822

Partition for the Hosmer and Lemeshow Test

Group	Total	co5passx = 1 Observed	co5passx = 1 Expected	co5passx = 0 Observed	co5passx = 0 Expected
1	76253	74930	74920.21	1323	1332.79
2	75939	75338	75366.96	601	572.04
3	76070	75765	75755.99	305	314.01
4	71758	71581	71575.21	177	182.79
5	73990	73849	73858.53	141	131.47
6	80503	80425	80403.39	78	99.61
7	68236	68195	68181.52	41	54.48
8	70115	70093	70084.25	22	30.75
9	69446	69435	69431.97	11	14.03
10	95633	95633	95623.44	0	9.56

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
23.4283	8	0.0029

NOTE: In calculating the Expected values, predicted probabilities less than 0.0001 and greater than 0.9999 were changed to 0.0001 and 0.9999 respectively.

Table C-7. SAS Output for Equations C-20 and C-29

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Model Information

Data Set	WORK.CLEAN1
Response Variable	nx2passx
Number of Response Levels	2
Number of Observations	771670
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	nx2passx	Total Frequency
1	1	755144
2	0	16526

NOTE: 8281 observations were deleted due to missing values for the response or explanatory variables.

Class Level Information

Design Variables

Class	Value	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
vMY	1986	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1987	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1988	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1989	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0				
	1990	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0				
	1991	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0				
	1992	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0				
	1993	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0				
	1994	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0				
	1995	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0				
	1996	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0				
	1997	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0				
	1999	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0				

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---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Class Level Information

Design Variables

Class	Value	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	2000	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0				
	2001	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0				
	2002	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1				

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Without Covariates	With Covariates
AIC	1069761.8	131794.90
SC	1069761.8	132083.81
-2 Log L	1069761.8	131744.90

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	938016.868	25	<.0001
Score	709603.944	25	<.0001
Wald	157905.646	25	<.0001

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---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Type III Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > ChiSq
vMY	16	127502.077	<.0001
del_t_veh_age	1	30.3268	<.0001
del_lctpt	1	4294.4207	<.0001
del_previnit_pass	1	3658.8054	<.0001
del_dsp_asm_gt90only	1	296.0014	<.0001
del_previnit_asm_exi	1	112.7408	<.0001
LE_90d_since_asm	1	721.4864	<.0001
del_previnit_tsi_exi	1	29.5607	<.0001
del_dsp_tsi_gt90only	1	29.7729	<.0001
LE_90d_since_tsi	1	0.1033	0.7479

Analysis of Maximum Likelihood Estimates

Parameter		DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
vMY	1986	1	3.3781	0.0363	8675.9701	<.0001
vMY	1987	1	2.9776	0.0226	17297.2836	<.0001
vMY	1988	1	3.0304	0.0217	19460.1211	<.0001
vMY	1989	1	3.2331	0.0218	22034.0769	<.0001
vMY	1990	1	3.4386	0.0217	25067.2366	<.0001
vMY	1991	1	3.9437	0.0280	19806.1937	<.0001
vMY	1992	1	4.0270	0.0274	21675.4758	<.0001
vMY	1993	1	4.3632	0.0386	12780.5709	<.0001
vMY	1994	1	5.0762	0.0486	10909.2463	<.0001
vMY	1995	1	4.4741	0.0306	21309.4504	<.0001
vMY	1996	1	6.4989	0.0637	10403.9474	<.0001
vMY	1997	1	7.4195	0.3783	384.6912	<.0001
vMY	1999	1	8.4274	0.3035	770.8139	<.0001
vMY	2000	1	8.6758	0.3345	672.8172	<.0001
vMY	2001	1	9.3504	0.5037	344.6428	<.0001
vMY	2002	1	17.4354	40.1270	0.1888	0.6639
del_t_veh_age		1	-1.1253	0.2043	30.3268	<.0001
del_lctpt		1	2.3693	0.0362	4294.4207	<.0001

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
del_previnit_pass	1	1.6695	0.0276	3658.8054	<.0001
del_dsp_asm_gt90only	1	-0.00087	0.000051	296.0014	<.0001
del_previnit_asm_exi	1	0.3593	0.0338	112.7408	<.0001
LE_90d_since_asm	1	1.4502	0.0540	721.4864	<.0001
del_previnit_tsi_exi	1	0.2126	0.0391	29.5607	<.0001
del_dsp_tsi_gt90only	1	-0.00070	0.000128	29.7729	<.0001
LE_90d_since_tsi	1	0.0954	0.2968	0.1033	0.7479

Odds Ratio Estimates

Effect		Point Estimate	95% Wald Confidence Limits	
vMY	1986 vs 2002	<0.001	<0.001	>999.999
vMY	1987 vs 2002	<0.001	<0.001	>999.999
vMY	1988 vs 2002	<0.001	<0.001	>999.999
vMY	1989 vs 2002	<0.001	<0.001	>999.999
vMY	1990 vs 2002	<0.001	<0.001	>999.999
vMY	1991 vs 2002	<0.001	<0.001	>999.999
vMY	1992 vs 2002	<0.001	<0.001	>999.999
vMY	1993 vs 2002	<0.001	<0.001	>999.999
vMY	1994 vs 2002	<0.001	<0.001	>999.999
vMY	1995 vs 2002	<0.001	<0.001	>999.999
vMY	1996 vs 2002	<0.001	<0.001	>999.999
vMY	1997 vs 2002	<0.001	<0.001	>999.999
vMY	1999 vs 2002	<0.001	<0.001	>999.999
vMY	2000 vs 2002	<0.001	<0.001	>999.999
vMY	2001 vs 2002	<0.001	<0.001	>999.999
del_t_veh_age		0.325	0.217	0.484
del_lctpt		10.690	9.958	11.475
del_previnit_pass		5.310	5.030	5.605
del_dsp_asm_gt90only		0.999	0.999	0.999
del_previnit_asm_exi		1.432	1.340	1.531
LE_90d_since_asm		4.264	3.836	4.740

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
del_previnit_tsi_exi	1.237	1.146	1.335
del_dsp_tsi_gt90only	0.999	0.999	1.000
LE_90d_since_tsi	1.100	0.615	1.968

Association of Predicted Probabilities and Observed Responses

Percent Concordant	83.1	Somers' D	0.676
Percent Discordant	15.5	Gamma	0.686
Percent Tied	1.4	Tau-a	0.028
Pairs	12479509744	c	0.838

Partition for the Hosmer and Lemeshow Test

		nx2passx = 1		nx2passx = 0	
Group	Total	Observed	Expected	Observed	Expected
1	77145	69455	69461.96	7690	7683.04
2	76950	73498	73622.78	3452	3327.22
3	77148	75036	74998.87	2112	2149.13
4	77668	76225	76214.58	1443	1453.42
5	76701	75778	75763.87	923	937.13
6	78136	77645	77574.89	491	561.11
7	76271	76014	75986.90	257	284.10
8	80375	80254	80251.31	121	123.69
9	85424	85396	85385.45	28	38.55
10	65852	65843	65844.92	9	7.08

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---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
20.7344	8	0.0079

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Table C-8. SAS Output for Equations C-21 and C-30

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----------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N -----------------------------------

The LOGISTIC Procedure

Model Information

Data Set	WORK.CLEAN1
Response Variable	nx5passx
Number of Response Levels	2
Number of Observations	771670
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	nx5passx	Total Frequency
1	1	753780
2	0	17890

NOTE: 8281 observations were deleted due to missing values for the response or explanatory variables.

Class Level Information

Design Variables

Class	Value	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
vMY	1986	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1987	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1988	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1989	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0				
	1990	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0				
	1991	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0				
	1992	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0				
	1993	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0				
	1994	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0				
	1995	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0				
	1996	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0				
	1997	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0				
	1999	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0				

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----------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N -----------------------------------

The LOGISTIC Procedure

Class Level Information

Design Variables

Class	Value	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	2000	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0				
	2001	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0				
	2002	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1				

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Without Covariates	With Covariates
AIC	1069761.8	137490.76
SC	1069761.8	137779.67
-2 Log L	1069761.8	137440.76

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	932321.007	25	<.0001
Score	704978.001	25	<.0001
Wald	158898.244	25	<.0001

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---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Type III Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > ChiSq
vMY	16	118627.387	<.0001
del_t_veh_age	1	47.8179	<.0001
del_lctpt	1	5045.3525	<.0001
del_previnit_pass	1	3258.5977	<.0001
del_dsp_asm_gt90only	1	384.9460	<.0001
del_previnit_asm_exi	1	53.9361	<.0001
LE_90d_since_asm	1	912.0214	<.0001
del_previnit_tsi_exi	1	12.2513	0.0005
del_dsp_tsi_gt90only	1	28.3075	<.0001
LE_90d_since_tsi	1	0.3515	0.5533

Analysis of Maximum Likelihood Estimates

Parameter		DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
vMY	1986	1	3.3471	0.0358	8727.3452	<.0001
vMY	1987	1	2.9784	0.0225	17589.0951	<.0001
vMY	1988	1	2.7540	0.0195	19883.9967	<.0001
vMY	1989	1	3.1062	0.0205	22876.2496	<.0001
vMY	1990	1	3.3742	0.0209	26038.7645	<.0001
vMY	1991	1	4.0727	0.0291	19585.0898	<.0001
vMY	1992	1	4.4076	0.0318	19170.6923	<.0001
vMY	1993	1	4.6842	0.0428	11987.6219	<.0001
vMY	1994	1	5.0982	0.0466	11983.9624	<.0001
vMY	1995	1	4.7905	0.0342	19608.1038	<.0001
vMY	1996	1	6.0635	0.0430	19885.4626	<.0001
vMY	1997	1	7.4240	0.2898	656.0898	<.0001
vMY	1999	1	7.7804	0.1731	2019.1650	<.0001
vMY	2000	1	8.1943	0.2165	1432.6859	<.0001
vMY	2001	1	9.2167	0.3426	723.6200	<.0001
vMY	2002	1	8.6220	0.4165	428.4340	<.0001
del_t_veh_age		1	-1.5567	0.2251	47.8179	<.0001
del_lctpt		1	2.4526	0.0345	5045.3525	<.0001

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
del_previnit_pass	1	1.5775	0.0276	3258.5977	<.0001
del_dsp_asm_gt90only	1	-0.00096	0.000049	384.9460	<.0001
del_previnit_asm_exi	1	0.2498	0.0340	53.9361	<.0001
LE_90d_since_asm	1	1.7841	0.0591	912.0214	<.0001
del_previnit_tsi_exi	1	0.1384	0.0395	12.2513	0.0005
del_dsp_tsi_gt90only	1	-0.00067	0.000127	28.3075	<.0001
LE_90d_since_tsi	1	0.1845	0.3112	0.3515	0.5533

Odds Ratio Estimates

Effect		Point Estimate	95% Wald Confidence Limits	
vMY	1986 vs 2002	0.005	0.002	0.012
vMY	1987 vs 2002	0.004	0.002	0.008
vMY	1988 vs 2002	0.003	0.001	0.006
vMY	1989 vs 2002	0.004	0.002	0.009
vMY	1990 vs 2002	0.005	0.002	0.012
vMY	1991 vs 2002	0.011	0.005	0.024
vMY	1992 vs 2002	0.015	0.007	0.033
vMY	1993 vs 2002	0.019	0.009	0.044
vMY	1994 vs 2002	0.029	0.013	0.067
vMY	1995 vs 2002	0.022	0.010	0.049
vMY	1996 vs 2002	0.077	0.034	0.175
vMY	1997 vs 2002	0.302	0.112	0.812
vMY	1999 vs 2002	0.431	0.181	1.026
vMY	2000 vs 2002	0.652	0.263	1.616
vMY	2001 vs 2002	1.812	0.645	5.094
del_t_veh_age		0.211	0.136	0.328
del_lctpt		11.618	10.858	12.431
del_previnit_pass		4.843	4.587	5.112
del_dsp_asm_gt90only		0.999	0.999	0.999
del_previnit_asm_exi		1.284	1.201	1.372
LE_90d_since_asm		5.954	5.303	6.685

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
del_previnit_tsi_exi	1.148	1.063	1.241
del_dsp_tsi_gt90only	0.999	0.999	1.000
LE_90d_since_tsi	1.203	0.654	2.213

Association of Predicted Probabilities and Observed Responses

Percent Concordant	84.2	Somers' D	0.697
Percent Discordant	14.5	Gamma	0.706
Percent Tied	1.3	Tau-a	0.032
Pairs	13485124200	c	0.848

Partition for the Hosmer and Lemeshow Test

		nx5passx = 1		nx5passx = 0	
Group	Total	Observed	Expected	Observed	Expected
1	77104	68099	68116.91	9005	8987.09
2	77418	73898	73997.89	3520	3420.11
3	77124	75047	75044.01	2077	2079.99
4	77535	76125	76126.50	1410	1408.50
5	77774	76858	76837.26	916	936.74
6	76542	76026	75964.55	516	577.45
7	78491	78213	78172.32	278	318.68
8	74811	74712	74680.31	99	130.69
9	80350	80301	80294.56	49	55.44
10	74521	74501	74507.64	20	13.36

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
27.1091	8	0.0007

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Table C-9. SAS Output for Equations C-22 and C-31

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---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Model Information

Data Set	WORK.CLEAN1
Response Variable	nx5passx
Number of Response Levels	2
Number of Observations	755144
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	nx5passx	Total Frequency
1	1	748604
2	0	6540

NOTE: 8281 observations were deleted due to missing values for the response or explanatory variables.

Class Level Information

Design Variables

Class	Value	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
vMY	1986	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1987	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1988	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0				
	1989	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0				
	1990	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0				
	1991	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0				
	1992	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0				
	1993	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0				
	1994	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0				
	1995	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0				
	1996	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0				
	1997	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0				
	1999	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0				

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---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Class Level Information

Design Variables

Class	Value	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	2000	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0				
	2001	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0				
	2002	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1				

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Without Covariates	With Covariates
AIC	1046851.9	62027.338
SC	1046851.9	62315.705
-2 Log L	1046851.9	61977.338

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	984874.531	25	<.0001
Score	729723.502	25	<.0001
Wald	98580.1912	25	<.0001

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---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Type III Analysis of Effects

Effect	DF	Wald Chi-Square	Pr > ChiSq
vMY	16	61671.4659	<.0001
del_t_veh_age	1	134.1042	<.0001
del_lctpt	1	1881.7942	<.0001
del_previnit_pass	1	1032.7160	<.0001
del_dsp_asm_gt90only	1	102.5843	<.0001
del_previnit_asm_exi	1	0.0384	0.8446
LE_90d_since_asm	1	310.6551	<.0001
del_previnit_tsi_exi	1	2.4133	0.1203
del_dsp_tsi_gt90only	1	16.9510	<.0001
LE_90d_since_tsi	1	0.0230	0.8795

Analysis of Maximum Likelihood Estimates

Parameter		DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
vMY	1986	1	4.5270	0.0622	5300.3755	<.0001
vMY	1987	1	3.9825	0.0356	12519.4886	<.0001
vMY	1988	1	3.6745	0.0298	15181.7785	<.0001
vMY	1989	1	4.1921	0.0337	15488.2571	<.0001
vMY	1990	1	4.4940	0.0350	16506.2389	<.0001
vMY	1991	1	5.6154	0.0592	8992.4365	<.0001
vMY	1992	1	5.9154	0.0643	8470.7304	<.0001
vMY	1993	1	5.8887	0.0737	6382.5573	<.0001
vMY	1994	1	6.2724	0.0785	6378.0911	<.0001
vMY	1995	1	6.2333	0.0653	9108.1489	<.0001
vMY	1996	1	6.7613	0.0605	12496.3385	<.0001
vMY	1997	1	8.6608	0.4495	371.2841	<.0001
vMY	1999	1	8.8839	0.2202	1627.0614	<.0001
vMY	2000	1	9.2244	0.2774	1105.8557	<.0001
vMY	2001	1	11.0284	0.4764	535.7897	<.0001
vMY	2002	1	10.0726	0.4586	482.3975	<.0001
del_t_veh_age		1	-4.5356	0.3917	134.1042	<.0001
del_lctpt		1	2.4134	0.0556	1881.7942	<.0001

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
del_previnit_pass	1	1.3972	0.0435	1032.7160	<.0001
del_dsp_asm_gt90only	1	-0.00078	0.000077	102.5843	<.0001
del_previnit_asm_exi	1	-0.0119	0.0606	0.0384	0.8446
LE_90d_since_asm	1	1.5606	0.0885	310.6551	<.0001
del_previnit_tsi_exi	1	-0.1089	0.0701	2.4133	0.1203
del_dsp_tsi_gt90only	1	-0.00088	0.000214	16.9510	<.0001
LE_90d_since_tsi	1	9.9127	65.3809	0.0230	0.8795

Odds Ratio Estimates

Effect		Point Estimate	95% Wald Confidence Limits	
vMY	1986 vs 2002	0.004	0.002	0.010
vMY	1987 vs 2002	0.002	<0.001	0.006
vMY	1988 vs 2002	0.002	<0.001	0.004
vMY	1989 vs 2002	0.003	0.001	0.007
vMY	1990 vs 2002	0.004	0.002	0.009
vMY	1991 vs 2002	0.012	0.005	0.029
vMY	1992 vs 2002	0.016	0.006	0.039
vMY	1993 vs 2002	0.015	0.006	0.038
vMY	1994 vs 2002	0.022	0.009	0.055
vMY	1995 vs 2002	0.022	0.009	0.053
vMY	1996 vs 2002	0.036	0.015	0.088
vMY	1997 vs 2002	0.244	0.071	0.840
vMY	1999 vs 2002	0.305	0.121	0.766
vMY	2000 vs 2002	0.428	0.159	1.156
vMY	2001 vs 2002	2.601	0.791	8.555
del_t_veh_age		0.011	0.005	0.023
del_lctpt		11.172	10.018	12.459
del_previnit_pass		4.044	3.714	4.404
del_dsp_asm_gt90only		0.999	0.999	0.999
del_previnit_asm_exi		0.988	0.878	1.113
LE_90d_since_asm		4.762	4.003	5.664

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
del_previnit_tsi_exi	0.897	0.782	1.029
del_dsp_tsi_gt90only	0.999	0.999	1.000
LE_90d_since_tsi	>999.999	<0.001	>999.999

Association of Predicted Probabilities and Observed Responses

Percent Concordant	84.2	Somers' D	0.717
Percent Discordant	12.5	Gamma	0.741
Percent Tied	3.2	Tau-a	0.012
Pairs	4895870160	c	0.859

Partition for the Hosmer and Lemeshow Test

Group	Total	nx5passx = 1 Observed	nx5passx = 1 Expected	nx5passx = 0 Observed	nx5passx = 0 Expected
1	75451	71820	71870.21	3631	3580.79
2	75369	74223	74200.57	1146	1168.43
3	74468	73715	73763.21	753	704.79
4	74826	74356	74358.53	470	467.47
5	73228	72947	72937.28	281	290.72
6	73833	73677	73654.98	156	178.02
7	69653	69597	69556.70	56	96.30
8	75812	75789	75756.02	23	55.98
9	75934	75920	75907.52	14	26.48
10	86570	86560	86561.34	10	8.66

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
49.9989	8	<.0001

NOTE: In calculating the Expected values, predicted probabilities less than 0.0001 and greater than 0.9999 were changed to 0.0001 and 0.9999 respectively.

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Table C-10. SAS Output for Equations C-2 and C-5

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Model Information

Data Set	WORK.HC_UNC
Response Variable	hcres_pass
Number of Response Levels	2
Number of Observations	794957
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	hcres_ pass	Total Frequency
1	1	760184
2	0	34773

NOTE: 206474 observations were deleted due to missing values for the response or explanatory variables.

Stepwise Selection Procedure

Step 0. Intercept entered:

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
54790.3319	6	<.0001

Step 1. Effect l_FprobHC entered:

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	285644.79	242592.57
SC	285656.38	242615.75
-2 Log L	285642.79	242588.57

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	43054.2162	1	<.0001
Score	37676.9120	1	<.0001
Wald	36324.0951	1	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
1074.0926	5	<.0001

Step 2. Effect l_FprobCO entered:

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	285644.79	242555.38
SC	285656.38	242590.14
-2 Log L	285642.79	242549.38

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	43093.4069	2	<.0001
Score	37989.4756	2	<.0001
Wald	36363.9765	2	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
1024.3124	4	<.0001

Step 3. Effect l_FprobHC*l_FprobCO entered:

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	285644.79	241731.09
SC	285656.38	241777.44
-2 Log L	285642.79	241723.09

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	43919.6973	3	<.0001
Score	49577.8826	3	<.0001
Wald	31771.5096	3	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
375.3301	3	<.0001

Step 4. Effect l_FprobNX entered:

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	285644.79	241683.33
SC	285656.38	241741.26
-2 Log L	285642.79	241673.33

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	43969.4642	4	<.0001
Score	50153.5189	4	<.0001
Wald	31948.0429	4	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
322.0422	2	<.0001

Step 5. Effect l_FprobCO*l_FprobNX entered:

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	285644.79	241360.62
SC	285656.38	241430.14
-2 Log L	285642.79	241348.62

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	44294.1665	5	<.0001
Score	50624.1969	5	<.0001
Wald	31732.8631	5	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
2.5641	1	0.1093

NOTE: No (additional) effects met the 0.05 significance level for entry into the model.

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Summary of Stepwise Selection

Step	Effect Entered	Effect Removed	DF	Number In	Score Chi-Square	Wald Chi-Square	Pr > ChiSq
1	l_FprobHC		1	1	37676.9120	.	<.0001
2	l_FprobCO		1	2	39.6994	.	<.0001
3	l_FprobHC*l_FprobCO		1	3	715.8257	.	<.0001
4	l_FprobNX		1	4	49.8549	.	<.0001
5	l_FprobCO*l_FprobNX		1	5	319.8735	.	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	1.2320	0.0268	2109.6548	<.0001
l_FprobHC	1	-1.0350	0.0221	2186.4643	<.0001
l_FprobCO	1	0.3428	0.0144	569.7011	<.0001
l_FprobNX	1	0.3620	0.0188	370.1152	<.0001
l_FprobHC*l_FprobCO	1	-0.0237	0.00635	13.8923	0.0002
l_FprobCO*l_FprobNX	1	0.1118	0.00625	319.7729	<.0001

Association of Predicted Probabilities and Observed Responses

Percent Concordant	80.2	Somers' D	0.613
Percent Discordant	18.9	Gamma	0.619
Percent Tied	0.9	Tau-a	0.051
Pairs	26433878232	c	0.806

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

Group	Total	hcres_pass = 1 Observed	hcres_pass = 1 Expected	hcres_pass = 0 Observed	hcres_pass = 0 Expected
1	79505	65352	65466.79	14153	14038.21
2	79647	72406	72578.41	7241	7068.59
3	79325	74799	74727.66	4526	4597.34
4	79707	76672	76510.70	3035	3196.30
5	79555	77457	77310.07	2098	2244.93
6	79489	78005	77942.88	1484	1546.12
7	79270	78193	78236.64	1077	1033.36
8	78292	77652	77642.19	640	649.81
9	80953	80579	80595.87	374	357.13
10	79214	79069	79132.89	145	81.11

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
81.0413	8	<.0001

Table C-11. SAS Output for Equations C-3 and C-6


```
---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

                                              The LOGISTIC Procedure

                                                Model Information

                                    Data Set                      WORK.CO_CON
                                    Response Variable             cores_pass
                                    Number of Response Levels     2
                                    Number of Observations        760184
                                    Link Function                 Logit
                                    Optimization Technique        Fisher's scoring


                                                 Response Profile

                                          Ordered     cores_          Total
                                            Value     pass         Frequency

                                                1           1        758659
                                                2           0          1525


                                           Stepwise Selection Procedure


Step  0. Intercept entered:


                                             Model Convergence Status

                                    Convergence criterion (GCONV=1E-8) satisfied.


                                             Residual Chi-Square Test

                                          Chi-Square       DF     Pr > ChiSq

                                           2184.3979        6         <.0001


Step  1. Effect l_FprobCO entered:
```



```
---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

                                              The LOGISTIC Procedure

                                             Model Convergence Status

                                    Convergence criterion (GCONV=1E-8) satisfied.


                                               Model Fit Statistics

                                                                 Intercept
                                                   Intercept        and
                                       Criterion        Only     Covariates

                                       AIC           21994.215      20514.836
                                       SC            22005.757      20537.918
                                       -2 Log L      21992.215      20510.836


                                       Testing Global Null Hypothesis: BETA=0

                               Test                 Chi-Square       DF     Pr > ChiSq

                               Likelihood Ratio      1481.3795        1         <.0001
                               Score                 1170.5478        1         <.0001
                               Wald                  1394.1531        1         <.0001


                                             Residual Chi-Square Test

                                          Chi-Square       DF     Pr > ChiSq

                                            285.0632        5         <.0001


Step  2. Effect l_FprobNX entered:


                                             Model Convergence Status

                                    Convergence criterion (GCONV=1E-8) satisfied.
```

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	21994.215	20336.435
SC	22005.757	20371.059
-2 Log L	21992.215	20330.435

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	1661.7807	2	<.0001
Score	1265.0029	2	<.0001
Wald	1579.9497	2	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
95.8054	4	<.0001

Step 3. Effect l_FprobCO*l_FprobNX entered:

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	21994.215	20236.741
SC	22005.757	20282.906
-2 Log L	21992.215	20228.741

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	1763.4743	3	<.0001
Score	1726.8737	3	<.0001
Wald	1467.0776	3	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
21.5077	3	<.0001

Step 4. Effect l_FprobHC entered:

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

The LOGISTIC Procedure

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	21994.215	20221.300
SC	22005.757	20279.007
-2 Log L	21992.215	20211.300

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	1780.9148	4	<.0001
Score	1805.4273	4	<.0001
Wald	1397.3144	4	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
4.1471	2	0.1257

NOTE: No (additional) effects met the 0.05 significance level for entry into the model.

The LOGISTIC Procedure

Summary of Stepwise Selection

Step	Effect Entered	Effect Removed	DF	Number In	Score Chi-Square	Wald Chi-Square	Pr > ChiSq
1	l_FprobCO		1	1	1170.5478	.	<.0001
2	l_FprobNX		1	2	186.9321	.	<.0001
3	l_FprobCO*l_FprobNX		1	3	79.2082	.	<.0001
4	l_FprobHC		1	4	16.9606	.	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	5.1752	0.1447	1278.5592	<.0001
l_FprobHC	1	0.3780	0.0917	16.9830	<.0001
l_FprobCO	1	-0.8248	0.0779	112.1110	<.0001
l_FprobNX	1	0.7470	0.0566	174.1594	<.0001
l_FprobCO*l_FprobNX	1	0.1132	0.0122	85.6753	<.0001

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
l_FprobHC	1.459	1.219	1.747

Association of Predicted Probabilities and Observed Responses

Percent Concordant	64.8	Somers' D	0.521
Percent Discordant	12.8	Gamma	0.671
Percent Tied	22.4	Tau-a	0.002
Pairs	1156954975	c	0.760

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

		cores_pass = 1		cores_pass = 0	
Group	Total	Observed	Expected	Observed	Expected
1	77575	76841	76935.64	734	639.36
2	79083	78841	78777.51	242	305.49
3	80247	80093	80048.90	154	198.10
4	79163	79063	79022.21	100	140.79
5	70234	70161	70145.19	73	88.81
6	79467	79416	79392.41	51	74.59
7	62147	62107	62104.16	40	42.84
8	93072	92979	93027.23	93	44.77
9	78411	78376	78388.33	35	22.67
10	60785	60782	60778.92	3	6.08

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
119.7678	8	<.0001

NOTE: In calculating the Expected values, predicted probabilities less than 0.0001 and greater than 0.9999 were changed to 0.0001 and 0.9999 respectively.

Table C-12. SAS Output for Equations C-4 and C-7

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Model Information

Data Set	WORK.NX_CON
Response Variable	nxres_pass
Number of Response Levels	2
Number of Observations	758659
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	nxres_ pass	Total Frequency
1	1	739127
2	0	19532

Stepwise Selection Procedure

Step 0. Intercept entered:

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
30165.5353	6	<.0001

Step 1. Effect l_FprobNX entered:

The LOGISTIC Procedure

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	181513.41	156462.11
SC	181524.95	156485.19
-2 Log L	181511.41	156458.11

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	25053.2986	1	<.0001
Score	19890.9555	1	<.0001
Wald	20599.0269	1	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
1160.8710	5	<.0001

Step 2. Effect l_FprobHC entered:

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

The LOGISTIC Procedure

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	181513.41	156054.52
SC	181524.95	156089.13
-2 Log L	181511.41	156048.52

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	25462.8931	2	<.0001
Score	20268.2485	2	<.0001
Wald	20902.6545	2	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
725.5181	4	<.0001

Step 3. Effect l_FprobHC*l_FprobNX entered:

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	181513.41	155541.53
SC	181524.95	155587.68
-2 Log L	181511.41	155533.53

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	25977.8819	3	<.0001
Score	28269.8170	3	<.0001
Wald	17861.0885	3	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
304.2643	3	<.0001

Step 4. Effect l_FprobCO entered:

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	181513.41	155476.31
SC	181524.95	155534.00
-2 Log L	181511.41	155466.31

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	26045.1001	4	<.0001
Score	29145.4421	4	<.0001
Wald	18065.7433	4	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
246.0297	2	<.0001

Step 5. Effect l_FprobCO*l_FprobNX entered:

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	181513.41	155411.43
SC	181524.95	155480.66
-2 Log L	181511.41	155399.43

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	26111.9792	5	<.0001
Score	29154.8936	5	<.0001
Wald	18166.0544	5	<.0001

Residual Chi-Square Test

Chi-Square	DF	Pr > ChiSq
180.4963	1	<.0001

Step 6. Effect l_FprobHC*l_FprobCO entered:

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	181513.41	155241.22
SC	181524.95	155321.99
-2 Log L	181511.41	155227.22

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	26284.1903	6	<.0001
Score	30165.5353	6	<.0001
Wald	17790.5663	6	<.0001

NOTE: All effects have been entered into the model.

Summary of Stepwise Selection

Step	Effect Entered	Effect Removed	DF	Number In	Score Chi-Square	Wald Chi-Square	Pr > ChiSq
1	l_FprobNX		1	1	19890.9555	.	<.0001
2	l_FprobHC		1	2	401.8621	.	<.0001
3	l_FprobHC*l_FprobNX		1	3	442.7522	.	<.0001
4	l_FprobCO		1	4	65.6027	.	<.0001
5	l_FprobCO*l_FprobNX		1	5	69.0754	.	<.0001
6	l_FprobHC*l_FprobCO		1	6	180.4963	.	<.0001

/bigrig/DecisionModel/ASMFprob2005/Build3rdASMFprobModels_fnte_1.sas 30JUL05 12:24

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	1.5607	0.0359	1885.3490	<.0001
l_FprobHC	1	-0.1054	0.0564	3.4886	0.0618
l_FprobCO	1	0.1839	0.0422	19.0314	<.0001
l_FprobNX	1	-0.4208	0.0297	200.9380	<.0001
l_FprobHC*l_FprobCO	1	-0.1183	0.00881	180.5118	<.0001
l_FprobHC*l_FprobNX	1	-0.0504	0.0163	9.5468	0.0020
l_FprobCO*l_FprobNX	1	0.2344	0.0167	197.8525	<.0001

Association of Predicted Probabilities and Observed Responses

Percent Concordant	80.3	Somers' D	0.620
Percent Discordant	18.2	Gamma	0.630
Percent Tied	1.5	Tau-a	0.031
Pairs	14436628564	c	0.810

Partition for the Hosmer and Lemeshow Test

		nxres_pass = 1		nxres_pass = 0	
Group	Total	Observed	Expected	Observed	Expected
1	75893	67570	67884.40	8323	8008.60
2	75893	71943	71867.62	3950	4025.38
3	76121	73576	73441.36	2545	2679.64
4	75388	73724	73560.91	1664	1827.09
5	75985	74814	74738.89	1171	1246.11
6	75118	74286	74298.62	832	819.38
7	75794	75278	75264.94	516	529.06
8	76248	75906	75956.26	342	291.74
9	77456	77316	77334.72	140	121.28
10	74763	74714	74741.42	49	21.58

---------------------------------- MET_ECS=FNTE Make_CarTrk=FORD_CAR Engine=3.0L_V6_N ----------------------------------

The LOGISTIC Procedure

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
88.8009	8	<.0001

Figure C-1. Linearization Check for Equations C-2 and C-5 (FNTE, FORD_CAR, 3.0L_V6_N)

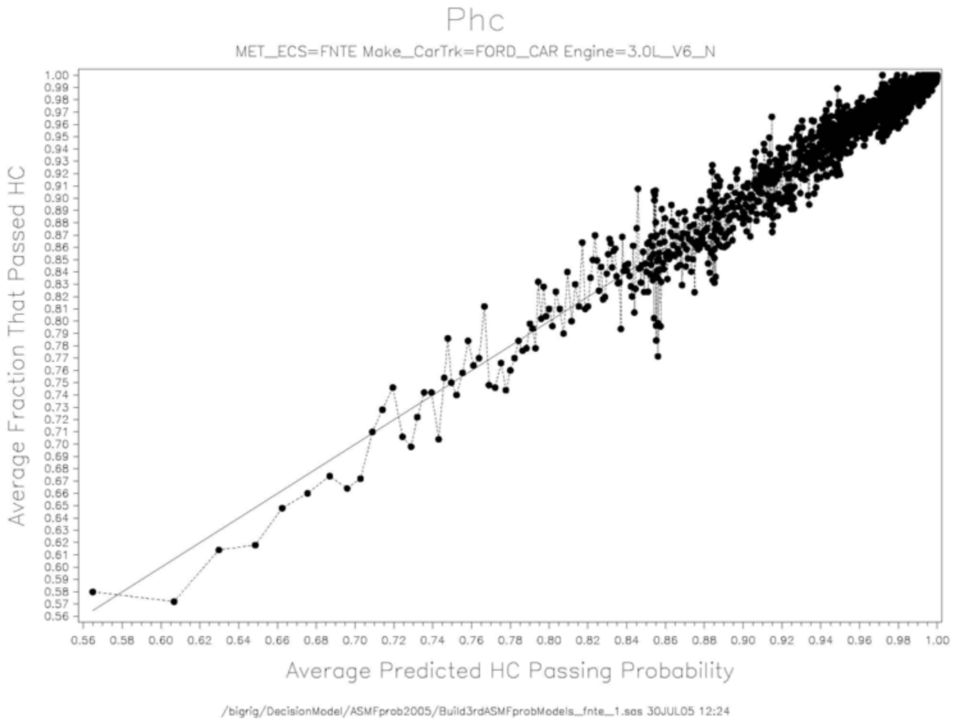


Figure C-2. Linearization Check for Equations C-3 and C-6 (FNTE, FORD_CAR, 3.0L_V6_N)

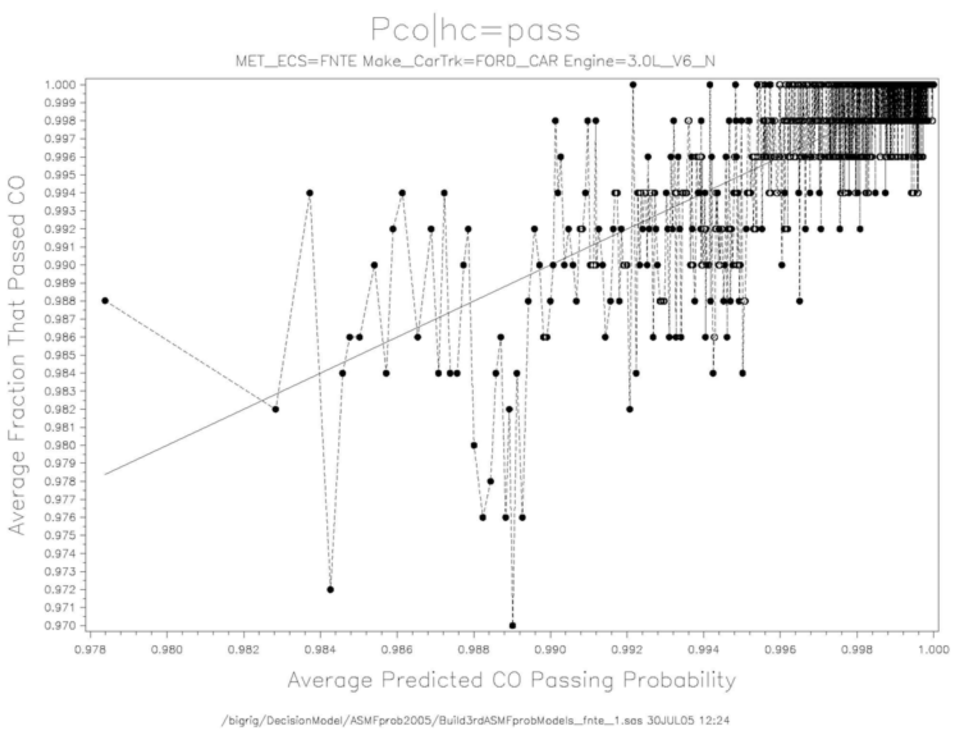
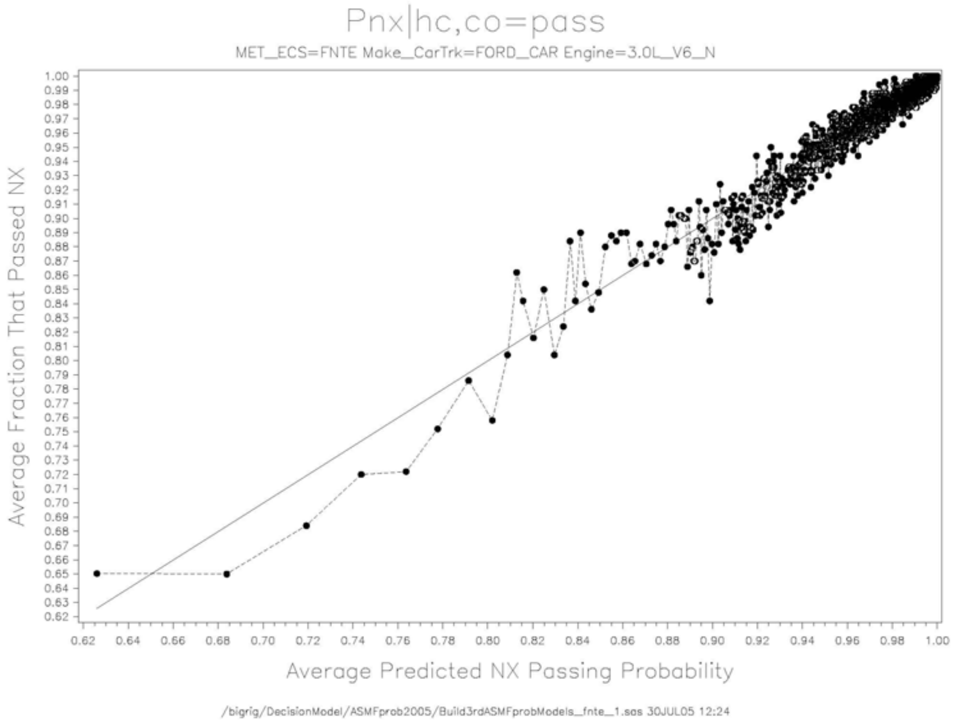


Figure C-3. Linearization Check for Equations C-4 and C-7 (FNTE, FORD_CAR, 3.0L_V6_N)



Appendix D

Model D ASM Failure Probability Equations

The following Model D equations can be used to calculate time-dependent overall ASM failure probability of a vehicle based on VID history, ASM cutpoints, and RSD measurements. None of the coefficients in these equations are vehicle-specific. However, inputs to these equations that are calculated using Model C equations are vehicle-specific. Equations D-8 through 13 can be used with calculus to estimate time-dependent average ASM emissions and with ASM-to-FTP relationships to estimate time-dependent average FTP emissions.

$$F_{\text{Overall Model D}} = 1 - (P_{HC}) * (P_{CO} \mid \text{HC Pass}) * (P_{NX} \mid \text{HC,CO Pass}) \quad \text{[D-1]}$$

where:

$$P_{HC} = \exp(\text{arg3\_HCunc}) / (1 + \exp(\text{arg3\_HCunc})) \quad \text{[D-2]}$$

$$P_{CO} \mid \text{HC Pass} = \exp(\text{arg3\_COcon}) / (1 + \exp(\text{arg3\_COcon})) \quad \text{[D-3]}$$

$$P_{NX} \mid \text{HC,CO Pass} = \exp(\text{arg3\_NXcon}) / (1 + \exp(\text{arg3\_NXcon})) \quad \text{[D-4]}$$

where:

$$\begin{aligned}
\text{arg3_HCunc} = \; & - 1.77372 \quad \text{[D-5]} \\
& - 0.75589 * \text{logit_}F_{HC}\text{_ModelC} \\
& + 0.13022 * \text{logit_}F_{CO}\text{_ModelC} \\
& + 0.00000 * \text{logit_}F_{NX}\text{_ModelC} \\
& + 0.00000 * \text{logit_}F_{HC}\text{_ModelC} * \text{logit_}F_{CO}\text{_ModelC} \\
& + 0.00000 * \text{logit_}F_{HC}\text{_ModelC} * \text{logit_}F_{NX}\text{_ModelC} \\
& + 0.00000 * \text{logit_}F_{CO}\text{_ModelC} * \text{logit_}F_{NX}\text{_ModelC} \\
& + 0.37443 * \text{arg_tRSDHC} \\
& + 0.32135 * \text{arg_tRSDCO} \\
& + 0.24707 * \text{arg_tRSDNX} \\
& + 0.00000 * \text{arg_tRSDHC} * \text{arg_tRSDCO} \\
& + 0.00000 * \text{arg_tRSDHC} * \text{arg_tRSDNX} \\
& + 0.00000 * \text{arg_tRSDCO} * \text{arg_tRSDNX}
\end{aligned}$$

$$\begin{aligned}
\text{arg3_COcon} = \; & + 0.59665 \quad \text{[D-6]} \\
& + 0.38664 * \text{logit_}F_{HC}\text{_ModelC} \\
& - 0.96245 * \text{logit_}F_{CO}\text{_ModelC} \\
& + 0.00000 * \text{logit_}F_{NX}\text{_ModelC} \\
& + 0.00000 * \text{logit_}F_{HC}\text{_ModelC} * \text{logit_}F_{CO}\text{_ModelC} \\
& + 0.00000 * \text{logit_}F_{HC}\text{_ModelC} * \text{logit_}F_{NX}\text{_ModelC} \\
& + 0.00000 * \text{logit_}F_{CO}\text{_ModelC} * \text{logit_}F_{NX}\text{_ModelC} \\
& + 0.00000 * \text{arg_tRSDHC} \\
& + 0.60122 * \text{arg_tRSDCO} \\
& + 0.00000 * \text{arg_tRSDNX} \\
& + 0.00000 * \text{arg_tRSDHC} * \text{arg_tRSDCO} \\
& + 0.00000 * \text{arg_tRSDHC} * \text{arg_tRSDNX} \\
& + 0.00000 * \text{arg_tRSDCO} * \text{arg_tRSDNX}
\end{aligned}$$

$$
\begin{aligned}
\text{arg3\_NXcon} = \; & -0.83349 && \text{[D-7]}\\
& + 0.23225 * \text{logit\_}F_{HC}\text{\_ModelC}\\
& + 0.08586 * \text{logit\_}F_{CO}\text{\_ModelC}\\
& - 0.86525 * \text{logit\_}F_{NX}\text{\_ModelC}\\
& + 0.00000 * \text{logit\_}F_{HC}\text{\_ModelC} * \text{logit\_}F_{CO}\text{\_ModelC}\\
& + 0.00000 * \text{logit\_}F_{HC}\text{\_ModelC} * \text{logit\_}F_{NX}\text{\_ModelC}\\
& + 0.00000 * \text{logit\_}F_{CO}\text{\_ModelC} * \text{logit\_}F_{NX}\text{\_ModelC}\\
& + 0.00000 * \text{arg\_tRSDHC}\\
& + 0.20758 * \text{arg\_tRSDCO}\\
& + 0.63355 * \text{arg\_tRSDNX}\\
& + 0.00000 * \text{arg\_tRSDHC} * \text{arg\_tRSDCO}\\
& + 0.00000 * \text{arg\_tRSDHC} * \text{arg\_tRSDNX}\\
& + 0.00000 * \text{arg\_tRSDCO} * \text{arg\_tRSDNX}
\end{aligned}
$$

$$P_{HC2} = \exp(\text{arg2\_HC2unc}) / (1 + \exp(\text{arg2\_HC2unc})) \quad \text{[D-8]}$$
$$P_{HC5} = \exp(\text{arg2\_HC5unc}) / (1 + \exp(\text{arg2\_HC5unc})) \quad \text{[D-9]}$$
$$P_{CO2} = \exp(\text{arg2\_CO2unc}) / (1 + \exp(\text{arg2\_CO2unc})) \quad \text{[D-10]}$$
$$P_{CO5} = \exp(\text{arg2\_CO5unc}) / (1 + \exp(\text{arg2\_CO5unc})) \quad \text{[D-11]}$$
$$P_{NX2} = \exp(\text{arg2\_NX2unc}) / (1 + \exp(\text{arg2\_NX2unc})) \quad \text{[D-12]}$$
$$P_{NX5} = \exp(\text{arg2\_NX5unc}) / (1 + \exp(\text{arg2\_NX5unc})) \quad \text{[D-13]}$$

where:

$$
\begin{aligned}
\text{arg2\_HC2unc} = \; & -2.23566 && \text{[D-14]}\\
& + 0.59621 * \text{logit\_}P_{HC2}\text{\_ModelC}\\
& + 0.55589 * \text{arg\_tRSDHC}\\
& + 0.35675 * \text{arg\_tRSDCO}\\
& + 0.36513 * \text{arg\_tRSDNX}\\
& + 0.00000 * \text{arg\_tRSDHC} * \text{arg\_tRSDCO}\\
& - 0.048447 * \text{arg\_tRSDHC} * \text{arg\_tRSDNX}\\
& + 0.00000 * \text{arg\_tRSDCO} * \text{arg\_tRSDNX}
\end{aligned}
$$

$$
\begin{aligned}
\text{arg2\_HC5unc} = \; & -2.47061 && \text{[D-15]}\\
& + 0.64254 * \text{logit\_}P_{HC5}\text{\_ModelC}\\
& + 0.70663 * \text{arg\_tRSDHC}\\
& + 0.39656 * \text{arg\_tRSDCO}\\
& + 0.37438 * \text{arg\_tRSDNX}\\
& - 0.05084 * \text{arg\_tRSDHC} * \text{arg\_tRSDCO}\\
& - 0.051278 * \text{arg\_tRSDHC} * \text{arg\_tRSDNX}\\
& + 0.00000 * \text{arg\_tRSDCO} * \text{arg\_tRSDNX}
\end{aligned}
$$

$$\begin{aligned}
\text{arg2_CO2unc} = \; & -1.61547 \\
& + 0.62148 * \text{logit_P}_{CO2}\text{_ModelC} \\
& + 0.60688 * \text{arg_tRSDHC} \\
& + 0.69848 * \text{arg_tRSDCO} \\
& - 0.15335 * \text{arg_tRSDNX} \\
& - 0.13802 * \text{arg_tRSDHC} * \text{arg_tRSDCO} \\
& + 0.00000 * \text{arg_tRSDHC} * \text{arg_tRSDNX} \\
& + 0.071847 * \text{arg_tRSDCO} * \text{arg_tRSDNX}
\end{aligned} \quad \text{[D-16]}$$

$$\begin{aligned}
\text{arg2_CO5unc} = \; & -1.75881 \\
& + 0.60043 * \text{logit_P}_{CO5}\text{_ModelC} \\
& + 0.62571 * \text{arg_tRSDHC} \\
& + 0.68342 * \text{arg_tRSDCO} \\
& - 0.06734 * \text{arg_tRSDNX} \\
& - 0.13695 * \text{arg_tRSDHC} * \text{arg_tRSDCO} \\
& + 0.00000 * \text{arg_tRSDHC} * \text{arg_tRSDNX} \\
& + 0.064571 * \text{arg_tRSDCO} * \text{arg_tRSDNX}
\end{aligned} \quad \text{[D-17]}$$

$$\begin{aligned}
\text{arg2_NX2unc} = \; & -2.10905 \\
& + 0.58857 * \text{logit_P}_{NX2}\text{_ModelC} \\
& - 0.12817 * \text{arg_tRSDHC} \\
& + 0.30308 * \text{arg_tRSDCO} \\
& + 1.10342 * \text{arg_tRSDNX} \\
& + 0.05570 * \text{arg_tRSDHC} * \text{arg_tRSDCO} \\
& + 0.00000 * \text{arg_tRSDHC} * \text{arg_tRSDNX} \\
& - 0.085294 * \text{arg_tRSDCO} * \text{arg_tRSDNX}
\end{aligned} \quad \text{[D-18]}$$

$$\begin{aligned}
\text{arg2_NX5unc} = \; & -2.12103 \\
& + 0.63591 * \text{logit_P}_{NX5}\text{_ModelC} \\
& - 0.18339 * \text{arg_tRSDHC} \\
& + 0.30868 * \text{arg_tRSDCO} \\
& + 1.02697 * \text{arg_tRSDNX} \\
& + 0.05810 * \text{arg_tRSDHC} * \text{arg_tRSDCO} \\
& + 0.00000 * \text{arg_tRSDHC} * \text{arg_tRSDNX} \\
& - 0.097876 * \text{arg_tRSDCO} * \text{arg_tRSDNX}
\end{aligned} \quad \text{[D-19]}$$

where:

P_{NX} | HC,CO Pass	denotes the fractional conditional Passing probability of ASM NX (that is, both ASM2525 NX and ASM5015 NX pass) given that ASM HC (both modes) and ASM CO (both modes) have already passed.
HC2	denotes ASM2525 HC
HC5	denotes ASM5015 HC
CO2	denotes ASM2525 CO
CO5	denotes ASM5015 CO
NX2	denotes ASM2525 NX
NX5	denotes ASM5015 NX
logit_F_{HC}_ModelC	is calculated by an engine-specific equation like Equation C-8
logit_F_{CO}_ModelC	is calculated by an engine-specific equation like Equation C-9
logit_F_{NX}_ModelC	is calculated by an engine-specific equation like Equation C-10
logit_P_{HC2}_ModelC	is calculated by an engine-specific equation like Equation C-23
logit_P_{HC5}_ModelC	is calculated by an engine-specific equation like Equation C-24
logit_P_{CO2}_ModelC	is calculated by an engine-specific equation like Equation C-26
logit_P_{CO5}_ModelC	is calculated by an engine-specific equation like Equation C-27
logit_P_{NX2}_ModelC	is calculated by an engine-specific equation like Equation C-29
logit_P_{NX5}_ModelC	is calculated by an engine-specific equation like Equation C-30
arg_tRSDHC	is calculated by Equation G-2
arg_tRSDCO	is calculated by Equation G-7
arg_tRSDNX	is calculated by Equation G-10

Table D-1. SAS Output for Equations D-8 and D-14

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                                      The LOGISTIC Procedure

                                        Model Information

                          Data Set                      WORK.HC2UNC
                          Response Variable             tr_hc2res_pass
                          Number of Response Levels     2
                          Number of Observations        271719
                          Link Function                 Logit
                          Optimization Technique        Fisher's scoring


                                         Response Profile

                               Ordered     tr_hc2res_        Total
                                 Value     pass          Frequency

                                     1           1          265030
                                     2           0            6689

NOTE: 133231 observations were deleted due to missing values for the response or explanatory variables.


                                     Model Convergence Status

                          Convergence criterion (GCONV=1E-8) satisfied.


                                      Model Fit Statistics

                                                      Intercept
                                        Intercept          and
                             Criterion       Only    Covariates

                             AIC        62770.146     46385.860
                             SC         62780.659     46448.935
                             -2 Log L   62768.146     46373.860
```

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                                      The LOGISTIC Procedure

                             Testing Global Null Hypothesis: BETA=0

                     Test                 Chi-Square       DF     Pr > ChiSq

                     Likelihood Ratio     16394.2867        5         <.0001
                     Score                19590.1680        5         <.0001
                     Wald                 11450.4478        5         <.0001


                             Analysis of Maximum Likelihood Estimates

                                                       Standard
           Parameter               DF     Estimate        Error     Chi-Square    Pr > ChiSq

           Intercept                1      -2.2357       0.0824       736.2867        <.0001
           l_Phc2_u_modelC          1       0.5962       0.0105      3212.6877        <.0001
           arg_tRSDHC               1       0.5559       0.0319       303.5210        <.0001
           arg_tRSDCO               1       0.3567       0.0140       651.3039        <.0001
           arg_tRSDNX               1       0.3651       0.0284       164.8487        <.0001
           arg_tRSDH*arg_tRSDNX     1      -0.0484       0.0109        19.6782        <.0001


                                      Odds Ratio Estimates

                                             Point          95% Wald
                       Effect              Estimate      Confidence Limits

                       l_Phc2_u_modelC        1.815       1.778       1.853
                       arg_tRSDCO             1.429       1.390       1.468


                  Association of Predicted Probabilities and Observed Responses

                    Percent Concordant          88.4    Somers' D    0.779
                    Percent Discordant          10.5    Gamma        0.788
                    Percent Tied                 1.1    Tau-a        0.037
                    Pairs                 1772785670    c            0.889
```

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The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

		tr_hc2res_pass = 1		tr_hc2res_pass = 0	
Group	Total	Observed	Expected	Observed	Expected
1	27153	22959	22972.83	4194	4180.17
2	27110	25967	25952.09	1143	1157.91
3	27222	26606	26662.20	616	559.80
4	27182	26831	26861.26	351	320.74
5	27228	27061	27031.89	167	196.11
6	26939	26842	26818.88	97	120.12
7	27413	27350	27336.74	63	76.26
8	27062	27033	27014.25	29	47.75
9	28477	28456	28446.30	21	30.70
10	25933	25925	25920.00	8	13.00

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
32.4083	8	<.0001

Table D-2. SAS Output for Equations D-9 and D-15

The LOGISTIC Procedure

Model Information

Data Set	WORK.HC5UNC
Response Variable	tr_hc5res_pass
Number of Response Levels	2
Number of Observations	271719
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	tr_hc5res_ pass	Total Frequency
1	1	264743
2	0	6976

NOTE: 133231 observations were deleted due to missing values for the response or explanatory variables.

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	64869.657	47999.046
SC	64880.169	48072.634
-2 Log L	64867.657	47985.046

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	16882.6108	6	<.0001
Score	21313.9555	6	<.0001
Wald	11652.6447	6	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	-2.4706	0.1066	537.5398	<.0001
l_Phc5_u_modelC	1	0.6425	0.0103	3927.3952	<.0001
arg_tRSDHC	1	0.7066	0.0467	229.3542	<.0001
arg_tRSDCO	1	0.3966	0.0257	238.9816	<.0001
arg_tRSDNX	1	0.3744	0.0280	178.6474	<.0001
arg_tRSDH*arg_tRSDCO	1	-0.0508	0.0103	24.4479	<.0001
arg_tRSDH*arg_tRSDNX	1	-0.0513	0.0104	24.1390	<.0001

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
l_Phc5_u_modelC	1.901	1.863	1.940

Association of Predicted Probabilities and Observed Responses

Percent Concordant	88.4	Somers' D	0.779
Percent Discordant	10.5	Gamma	0.787
Percent Tied	1.0	Tau-a	0.039
Pairs	1846847168	c	0.889

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

		tr_hc5res_pass = 1		tr_hc5res_pass = 0	
Group	Total	Observed	Expected	Observed	Expected
1	27169	22910	22875.68	4259	4293.32
2	27163	25817	25934.97	1346	1228.03
3	27057	26430	26452.95	627	604.05
4	27447	27104	27093.16	343	353.84
5	27201	27008	26986.86	193	214.14
6	26993	26894	26863.21	99	129.79
7	26508	26449	26429.59	59	78.41
8	28581	28552	28530.21	29	50.79
9	25794	25784	25768.25	10	25.75
10	27806	27795	27794.37	11	11.63

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
46.7268	8	<.0001

Table D-3. SAS Output for Equations D-10 and D-16

The LOGISTIC Procedure

Model Information

Data Set	WORK.CO2UNC
Response Variable	tr_co2res_pass
Number of Response Levels	2
Number of Observations	271719
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	tr_co2res_ pass	Total Frequency
1	1	268351
2	0	3368

NOTE: 133231 observations were deleted due to missing values for the response or explanatory variables.

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	36270.146	26479.334
SC	36280.659	26552.922
-2 Log L	36268.146	26465.334

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	9802.8119	6	<.0001
Score	14103.3367	6	<.0001
Wald	7361.1212	6	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	-1.6155	0.1503	115.5833	<.0001
l_Pco2_u_modelC	1	0.6215	0.0127	2388.2477	<.0001
arg_tRSDHC	1	0.6069	0.0498	148.2838	<.0001
arg_tRSDCO	1	0.6985	0.0495	198.7972	<.0001
arg_tRSDNX	1	-0.1534	0.0424	13.1125	0.0003
arg_tRSDH*arg_tRSDCO	1	-0.1380	0.0137	101.9895	<.0001
arg_tRSDC*arg_tRSDNX	1	0.0718	0.0128	31.4839	<.0001

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
l_Pco2_u_modelC	1.862	1.816	1.909

Association of Predicted Probabilities and Observed Responses

Percent Concordant	88.9	Somers' D	0.800
Percent Discordant	8.9	Gamma	0.818
Percent Tied	2.2	Tau-a	0.020
Pairs	903806168	c	0.900

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

		tr_co2res_pass = 1		tr_co2res_pass = 0	
Group	Total	Observed	Expected	Observed	Expected
1	27184	24923	24915.20	2261	2268.80
2	27296	26742	26802.12	554	493.88
3	26905	26663	26649.72	242	255.28
4	27137	27002	26984.12	135	152.88
5	26322	26241	26232.89	81	89.11
6	28003	27948	27946.91	55	56.09
7	26546	26520	26514.72	26	31.28
8	30394	30386	30373.18	8	20.82
9	21951	21947	21942.23	4	8.77
10	29981	29979	29976.42	2	4.58

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
23.8792	8	0.0024

Table D-4. SAS Output for Equations D-11 and D-17

The LOGISTIC Procedure

Model Information

Data Set	WORK.CO5UNC
Response Variable	tr_co5res_pass
Number of Response Levels	2
Number of Observations	271719
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	tr_co5res_ pass	Total Frequency
1	1	268121
2	0	3598

NOTE: 133231 observations were deleted due to missing values for the response or explanatory variables.

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	38268.458	28529.687
SC	38278.970	28603.275
-2 Log L	38266.458	28515.687

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	9750.7706	6	<.0001
Score	13899.6985	6	<.0001
Wald	7384.8468	6	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	-1.7588	0.1465	144.1152	<.0001
l_Pco5_u_modelC	1	0.6004	0.0127	2224.0676	<.0001
arg_tRSDHC	1	0.6257	0.0490	162.9836	<.0001
arg_tRSDCO	1	0.6834	0.0474	207.9026	<.0001
arg_tRSDNX	1	-0.0673	0.0413	2.6543	0.1033
arg_tRSDH*arg_tRSDCO	1	-0.1370	0.0133	106.8140	<.0001
arg_tRSDC*arg_tRSDNX	1	0.0646	0.0124	27.3309	<.0001

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
l_Pco5_u_modelC	1.823	1.778	1.869

Association of Predicted Probabilities and Observed Responses

Percent Concordant	88.1	Somers' D	0.783
Percent Discordant	9.7	Gamma	0.801
Percent Tied	2.2	Tau-a	0.020
Pairs	964699358	c	0.892

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The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

Group	Total	tr_co5res_pass = 1 Observed	tr_co5res_pass = 1 Expected	tr_co5res_pass = 0 Observed	tr_co5res_pass = 0 Expected
1	27188	24871	24849.29	2317	2338.71
2	27302	26653	26745.84	649	556.16
3	27057	26795	26765.63	262	291.37
4	27034	26877	26860.21	157	173.79
5	26411	26327	26307.06	84	103.94
6	27024	26959	26958.80	65	65.20
7	25686	25646	25647.83	40	38.17
8	28945	28928	28919.14	17	25.86
9	25545	25542	25532.07	3	12.93
10	29527	29523	29522.05	4	4.95

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
35.4412	8	<.0001

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Table D-5. SAS Output for Equations D-12 and D-18

The LOGISTIC Procedure

Model Information

Data Set	WORK.NX2UNC
Response Variable	tr_nx2res_pass
Number of Response Levels	2
Number of Observations	271719
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	tr_nx2res_ pass	Total Frequency
1	1	264978
2	0	6741

NOTE: 133231 observations were deleted due to missing values for the response or explanatory variables.

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	63152.388	45559.453
SC	63162.901	45633.041
-2 Log L	63150.388	45545.453

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	17604.9348	6	<.0001
Score	18445.0779	6	<.0001
Wald	10313.5700	6	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	-2.1090	0.1298	263.9446	<.0001
l_Pnx2_u_modelC	1	0.5886	0.00990	3537.4720	<.0001
arg_tRSDHC	1	-0.1282	0.0423	9.1665	0.0025
arg_tRSDCO	1	0.3031	0.0375	65.4352	<.0001
arg_tRSDNX	1	1.1034	0.0452	595.3837	<.0001
arg_tRSDH*arg_tRSDCO	1	0.0557	0.0111	25.1277	<.0001
arg_tRSDC*arg_tRSDNX	1	-0.0853	0.0119	51.6444	<.0001

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
l_Pnx2_u_modelC	1.801	1.767	1.837

Association of Predicted Probabilities and Observed Responses

Percent Concordant	89.1	Somers' D	0.794
Percent Discordant	9.7	Gamma	0.804
Percent Tied	1.2	Tau-a	0.038
Pairs	1786216698	c	0.897

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

		tr_nx2res_pass = 1		tr_nx2res_pass = 0	
Group	Total	Observed	Expected	Observed	Expected
1	27170	22842	22916.93	4328	4253.07
2	27229	26003	25941.03	1226	1287.97
3	27179	26605	26580.21	574	598.79
4	27265	26997	26964.24	268	300.76
5	26707	26556	26556.30	151	150.70
6	27547	27450	27466.19	97	80.81
7	28780	28730	28735.75	50	44.25
8	26951	26926	26928.88	25	22.12
9	27549	27541	27537.02	8	11.98
10	25342	25328	25338.12	14	3.88

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
41.4860	8	<.0001

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Table D-6. SAS Output for Equations D-13 and D-19

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The LOGISTIC Procedure

Model Information

Data Set	WORK.NX5UNC
Response Variable	tr_nx5res_pass
Number of Response Levels	2
Number of Observations	271719
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	tr_nx5res_ pass	Total Frequency
1	1	261852
2	0	9867

NOTE: 133231 observations were deleted due to missing values for the response or explanatory variables.

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	84802.789	62848.372
SC	84813.302	62921.960
-2 Log L	84800.789	62834.372

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The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	21966.4168	6	<.0001
Score	21336.4549	6	<.0001
Wald	13575.8439	6	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	-2.1210	0.1102	370.3749	<.0001
l_Pnx5_u_modelC	1	0.6359	0.00870	5348.6907	<.0001
arg_tRSDHC	1	-0.1834	0.0349	27.6285	<.0001
arg_tRSDCO	1	0.3087	0.0315	96.2097	<.0001
arg_tRSDNX	1	1.0270	0.0376	746.5255	<.0001
arg_tRSDH*arg_tRSDCO	1	0.0581	0.00907	41.0552	<.0001
arg_tRSDC*arg_tRSDNX	1	-0.0979	0.00953	105.4644	<.0001

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
l_Pnx5_u_modelC	1.889	1.857	1.921

Association of Predicted Probabilities and Observed Responses

Percent Concordant	87.3	Somers' D	0.755
Percent Discordant	11.8	Gamma	0.761
Percent Tied	0.8	Tau-a	0.053
Pairs	2583693684	c	0.878

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

Group	Total	tr_nx5res_pass = 1 Observed	tr_nx5res_pass = 1 Expected	tr_nx5res_pass = 0 Observed	tr_nx5res_pass = 0 Expected
1	27175	21549	21606.46	5626	5568.54
2	27201	25291	25213.34	1910	1987.66
3	27127	26128	26091.85	999	1035.15
4	27086	26504	26505.38	582	580.62
5	27238	26904	26904.78	334	333.22
6	27551	27339	27362.08	212	188.92
7	26639	26532	26539.51	107	99.49
8	26173	26109	26121.20	64	51.80
9	28665	28635	28637.79	30	27.21
10	26864	26861	26855.59	3	8.41

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
15.3888	8	0.0520

Table D-7. SAS Output for Equations D-2 and D-5

The LOGISTIC Procedure

Model Information

Data Set	WORK.HCUNC
Response Variable	tr_hcres_pass
Number of Response Levels	2
Number of Observations	271719
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	tr_hcres_ pass	Total Frequency
1	1	263001
2	0	8718

NOTE: 133231 observations were deleted due to missing values for the response or explanatory variables.

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	77124.251	57111.476
SC	77134.763	57174.551
-2 Log L	77122.251	57099.476

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	20022.7750	5	<.0001
Score	20050.8382	5	<.0001
Wald	13590.7527	5	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	-1.7737	0.0427	1725.7152	<.0001
l_Fhc_u_modelC	1	-0.7559	0.0124	3743.6821	<.0001
l_Fco_u_modelC	1	0.1302	0.00854	232.5880	<.0001
arg_tRSDHC	1	0.3744	0.0144	672.0218	<.0001
arg_tRSDCO	1	0.3214	0.0124	667.5135	<.0001
arg_tRSDNX	1	0.2471	0.0112	490.1472	<.0001

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
l_Fhc_u_modelC	0.470	0.458	0.481
l_Fco_u_modelC	1.139	1.120	1.158
arg_tRSDHC	1.454	1.414	1.496
arg_tRSDCO	1.379	1.346	1.413
arg_tRSDNX	1.280	1.253	1.309

Association of Predicted Probabilities and Observed Responses

Percent Concordant	87.9	Somers' D	0.766
Percent Discordant	11.3	Gamma	0.773
Percent Tied	0.9	Tau-a	0.048
Pairs	2292842718	c	0.883

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

		tr_hcres_pass = 1		tr_hcres_pass = 0	
Group	Total	Observed	Expected	Observed	Expected
1	27185	22065	22017.35	5120	5167.65
2	27191	25505	25569.00	1686	1622.00
3	27202	26359	26399.22	843	802.78
4	27089	26580	26628.76	509	460.24
5	27136	26880	26853.92	256	282.08
6	27623	27487	27447.24	136	175.76
7	26942	26865	26838.12	77	103.88
8	27512	27461	27447.62	51	64.38
9	26954	26927	26917.30	27	36.70
10	26885	26872	26868.90	13	16.10

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
34.9847	8	<.0001

Table D-8. SAS Output for Equations D-3 and D-6

The LOGISTIC Procedure

Model Information

Data Set	WORK.COCON
Response Variable	tr_cores_pass
Number of Response Levels	2
Number of Observations	263001
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	tr_cores_ pass	Total Frequency
1	1	262132
2	0	869

NOTE: 141949 observations were deleted due to missing values for the response or explanatory variables.

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	11665.572	9257.169
SC	11676.052	9299.089
-2 Log L	11663.572	9249.169

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	2414.4029	3	<.0001
Score	2037.7274	3	<.0001
Wald	1928.0815	3	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	0.5967	0.0994	36.0331	<.0001
l_Fhc_u_modelC	1	0.3866	0.0339	130.3709	<.0001
l_Fco_u_modelC	1	-0.9624	0.0360	714.1921	<.0001
arg_tRSDCO	1	0.6012	0.0288	435.8855	<.0001

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
l_Fhc_u_modelC	1.472	1.378	1.573
l_Fco_u_modelC	0.382	0.356	0.410
arg_tRSDCO	1.824	1.724	1.930

Association of Predicted Probabilities and Observed Responses

Percent Concordant	82.1	Somers' D	0.744
Percent Discordant	7.7	Gamma	0.829
Percent Tied	10.3	Tau-a	0.005
Pairs	227792708	c	0.872

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

Group	Total	tr_cores_pass = 1 Observed	tr_cores_pass = 1 Expected	tr_cores_pass = 0 Observed	tr_cores_pass = 0 Expected
1	26164	25554	25594.94	610	569.06
2	26944	26825	26810.75	119	133.25
3	26411	26377	26341.48	34	69.52
4	24141	24111	24101.43	30	39.57
5	28434	28406	28404.30	28	29.70
6	26599	26569	26581.50	30	17.50
7	27120	27114	27108.87	6	11.13
8	20680	20671	20674.49	9	5.51
9	30932	30930	30926.86	2	5.14
10	25576	25575	25573.44	1	2.56

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
41.5390	8	<.0001

NOTE: In calculating the Expected values, predicted probabilities less than 0.0001 and greater than 0.9999 were changed to 0.0001 and 0.9999 respectively.

Table D-9. SAS Output for Equations D-4 and D-7


```
                    The LOGISTIC Procedure

                      Model Information

        Data Set                      WORK.NXCON
        Response Variable             tr_nxres_pass
        Number of Response Levels     2
        Number of Observations        262132
        Link Function                 Logit
        Optimization Technique        Fisher's scoring


                       Response Profile

              Ordered     tr_nxres_         Total
                Value     pass          Frequency

                    1            1         254410
                    2            0           7722

NOTE: 142818 observations were deleted due to missing values for the response or explanatory variables.


                   Model Convergence Status

        Convergence criterion (GCONV=1E-8) satisfied.


                    Model Fit Statistics

                                            Intercept
                             Intercept            and
           Criterion          Only         Covariates

           AIC             69652.877        52692.354
           SC              69663.353        52755.214
           -2 Log L        69650.877        52680.354
```



```
                    The LOGISTIC Procedure

           Testing Global Null Hypothesis: BETA=0

   Test                 Chi-Square       DF     Pr > ChiSq

   Likelihood Ratio     16970.5222        5         <.0001
   Score                12940.3757        5         <.0001
   Wald                 10863.7970        5         <.0001


           Analysis of Maximum Likelihood Estimates

                                        Standard
Parameter         DF     Estimate         Error     Chi-Square    Pr > ChiSq

Intercept          1      -0.8335        0.0496       281.9537        <.0001
l_Fhc_u_modelC     1       0.2322        0.0138       284.3019        <.0001
l_Fco_u_modelC     1       0.0859        0.0110        61.4421        <.0001
l_Fnx_u_modelC     1      -0.8653        0.0121      5080.7489        <.0001
arg_tRSDCO         1       0.2076        0.0110       353.7826        <.0001
arg_tRSDNX         1       0.6336        0.0121      2723.9851        <.0001


                     Odds Ratio Estimates

                           Point          95% Wald
           Effect       Estimate      Confidence Limits

           l_Fhc_u_modelC    1.261       1.228       1.296
           l_Fco_u_modelC    1.090       1.067       1.113
           l_Fnx_u_modelC    0.421       0.411       0.431
           arg_tRSDCO        1.231       1.204       1.258
           arg_tRSDNX        1.884       1.840       1.930


      Association of Predicted Probabilities and Observed Responses

         Percent Concordant         87.0    Somers' D    0.750
         Percent Discordant         12.0    Gamma        0.757
         Percent Tied                1.0    Tau-a        0.043
         Pairs                1964554020    c            0.875
```

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

Group	Total	tr_nxres_pass = 1 Observed	tr_nxres_pass = 1 Expected	tr_nxres_pass = 0 Observed	tr_nxres_pass = 0 Expected
1	26235	21832	21894.04	4403	4340.96
2	26257	24732	24730.96	1525	1526.04
3	26221	25460	25401.25	761	819.75
4	26246	25802	25775.37	444	470.63
5	26213	25951	25943.40	262	269.60
6	26190	26038	26038.61	152	151.39
7	27034	26941	26949.07	93	84.93
8	26919	26863	26875.13	56	43.87
9	25741	25721	25720.14	20	20.86
10	25076	25070	25068.71	6	7.29

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
11.5510	8	0.1724

/bigrig/DecisionModel/RSDFprob2005/D6.sas 31JUL05 12:30

Figure D-1. Linearization Check for Equations D-8 and D-14 (Training Dataset)

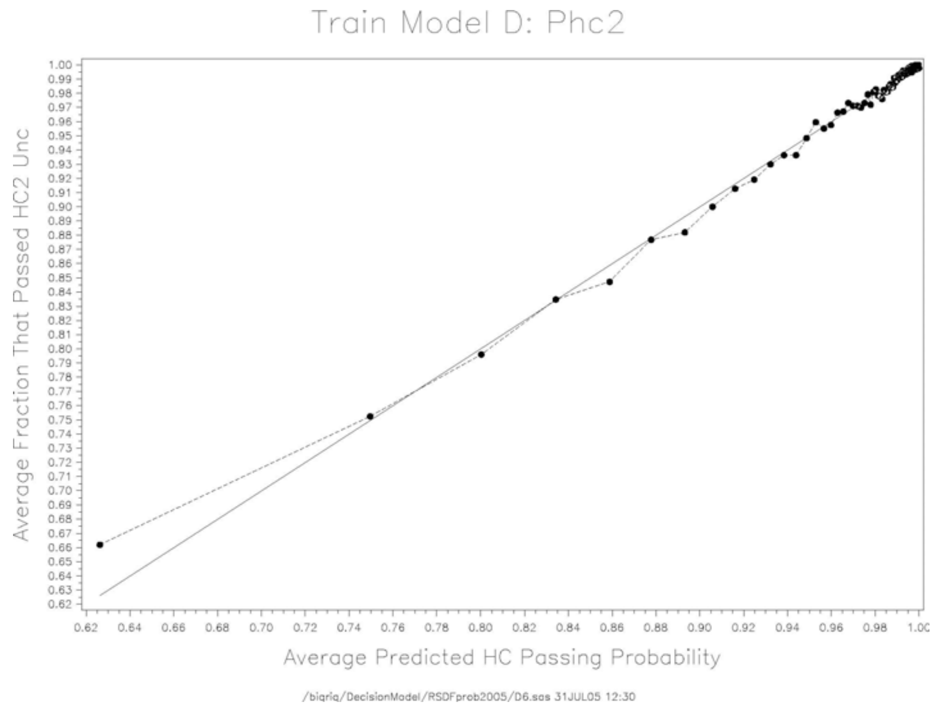


Figure D-2. Linearization Check for Equations D-9 and D-15 (Training Dataset)

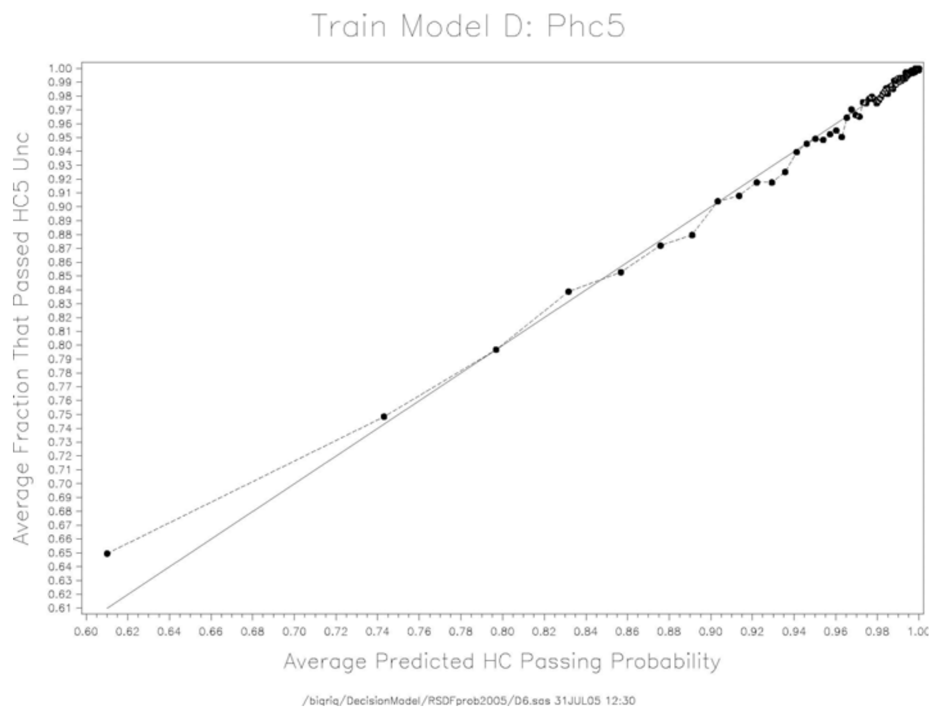


Figure D-3. Linearization Check for Equations D-10 and D-16 (Training Dataset)

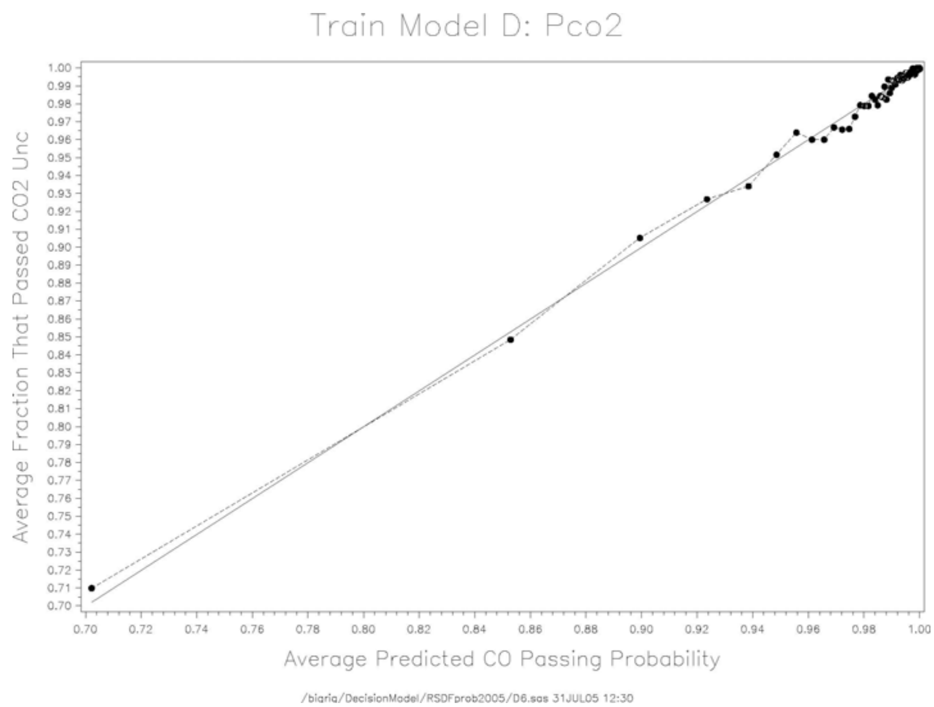


Figure D-4. Linearization Check for Equations D-11 and D-17 (Training Dataset)

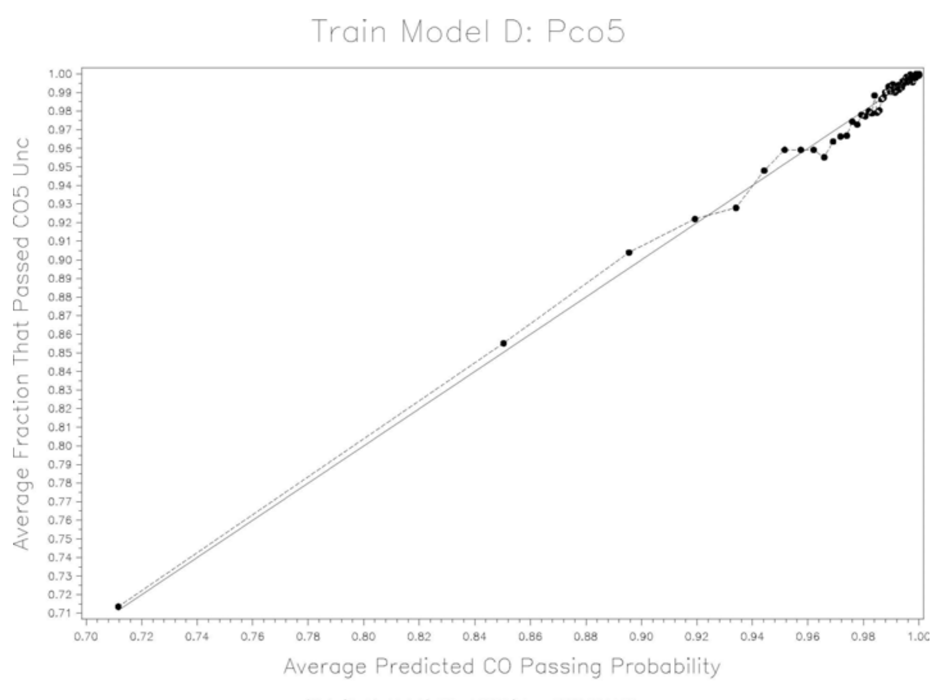


Figure D-5. Linearization Check for Equations D-12 and D-18 (Training Dataset)

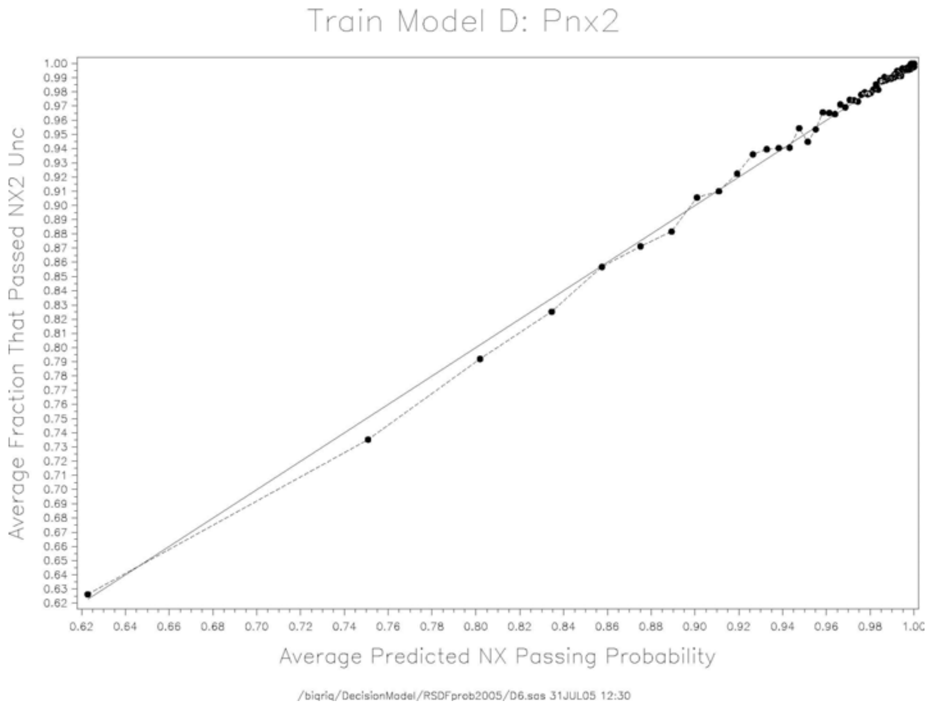


Figure D-6. Linearization Check for Equations D-13 and D-19 (Training Dataset)

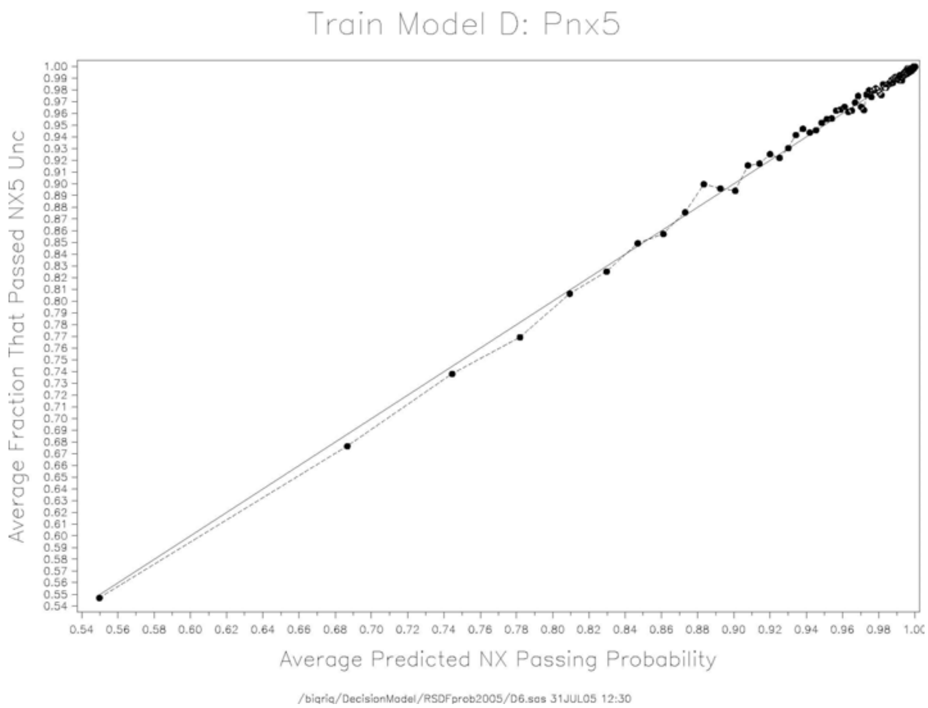


Figure D-7. Linearization Check for Equations D-8 and D-14 (Validation Dataset)

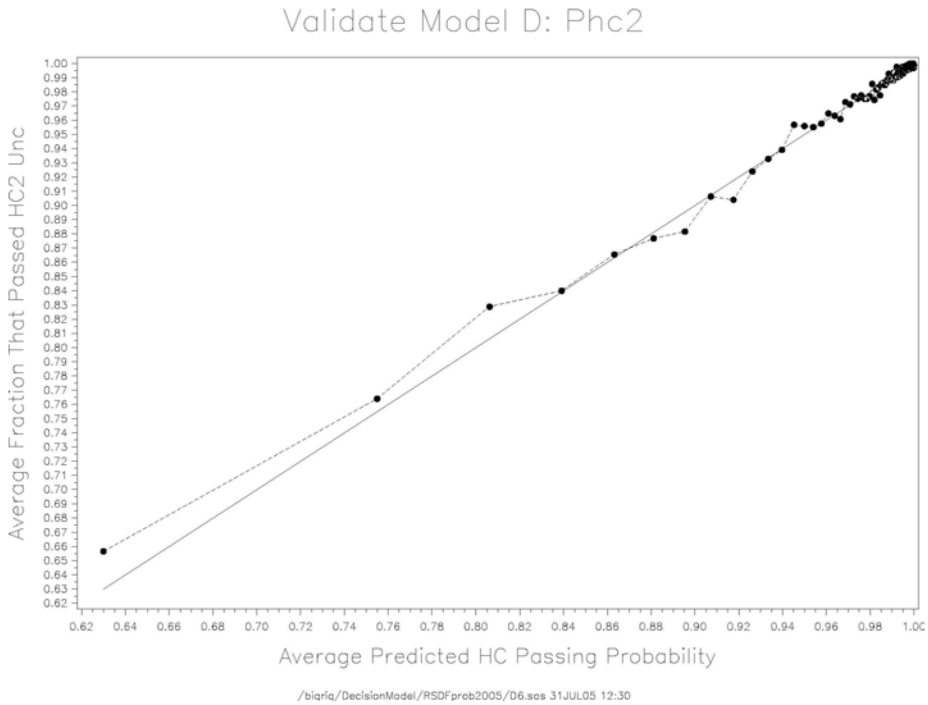


Figure D-8. Linearization Check for Equations D-9 and D-15 (Validation Dataset)

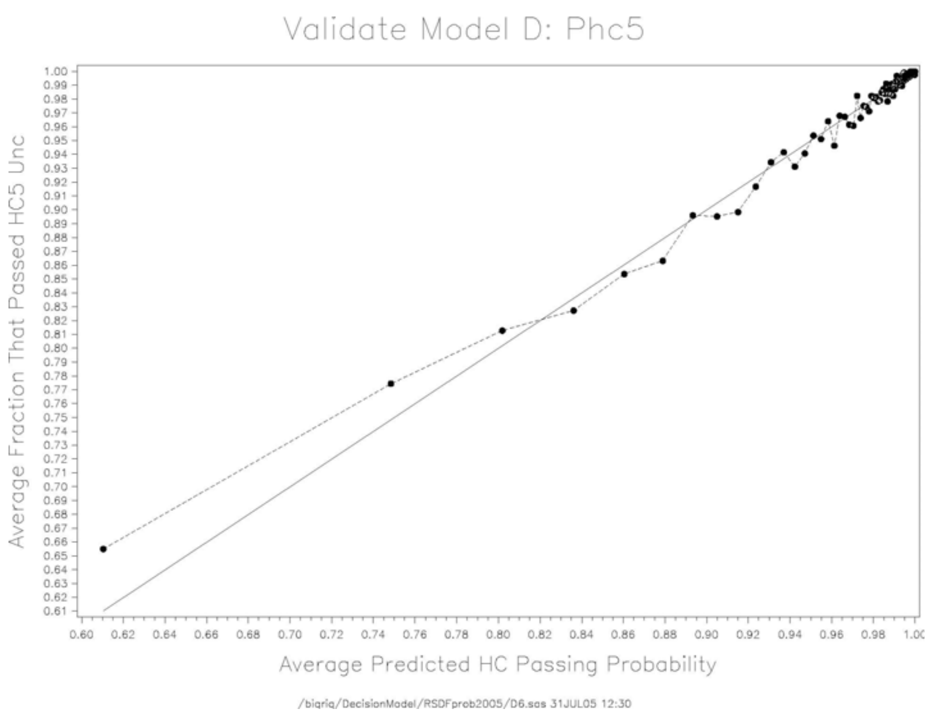


Figure D-9. Linearization Check for Equations D-10 and D-16 (Validation Dataset)

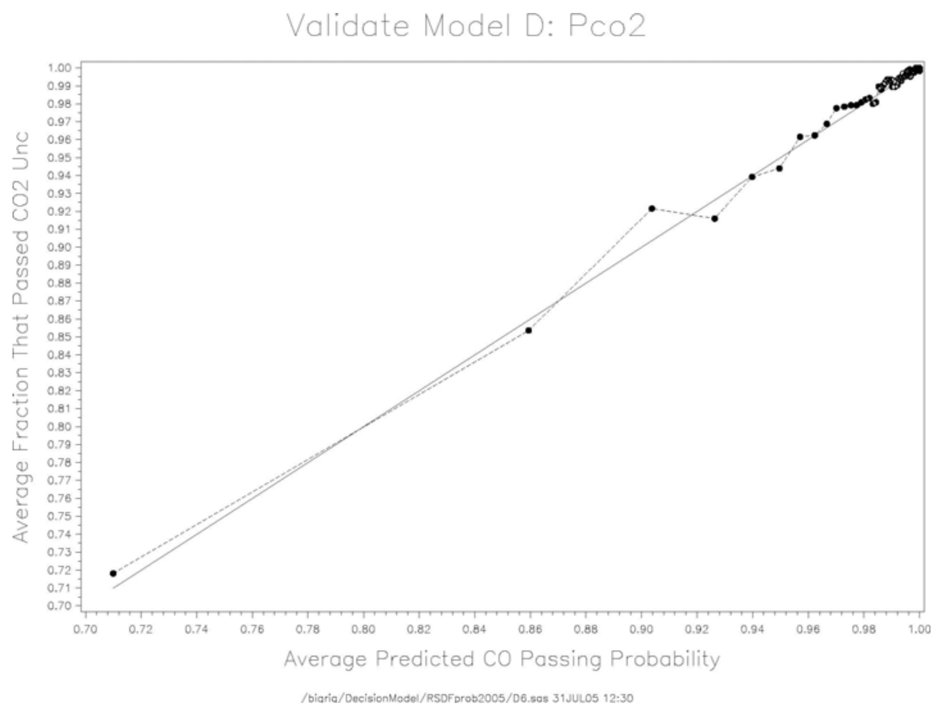


Figure D-10. Linearization Check for Equations D-11 and D-17 (Validation Dataset)

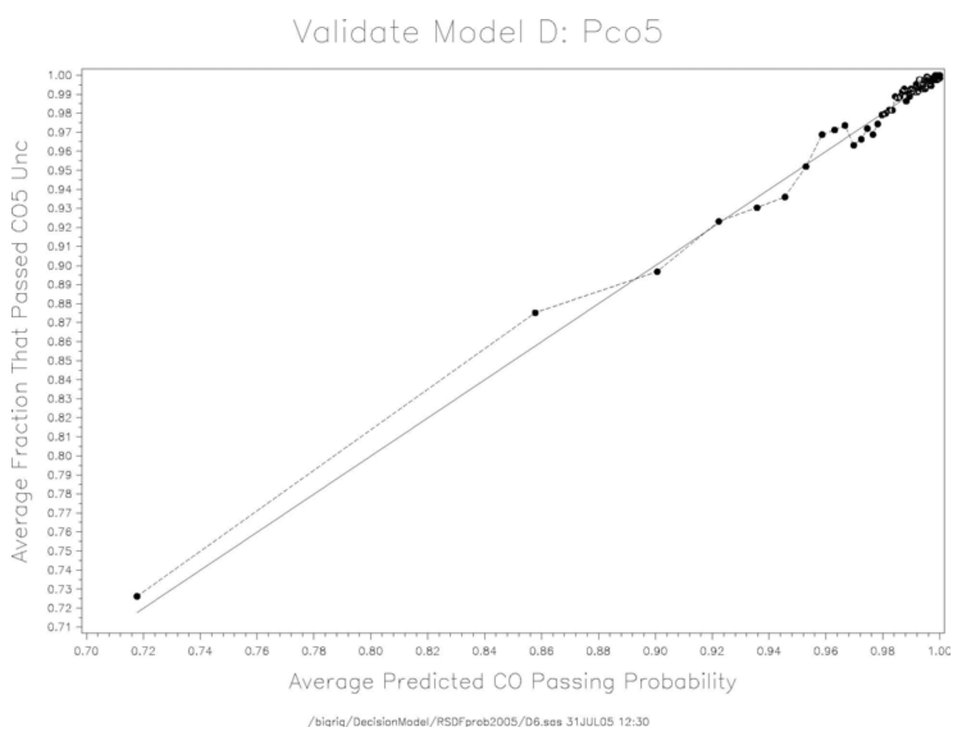


Figure D-11. Linearization Check for Equations D-12 and D-18 (Validation Dataset)

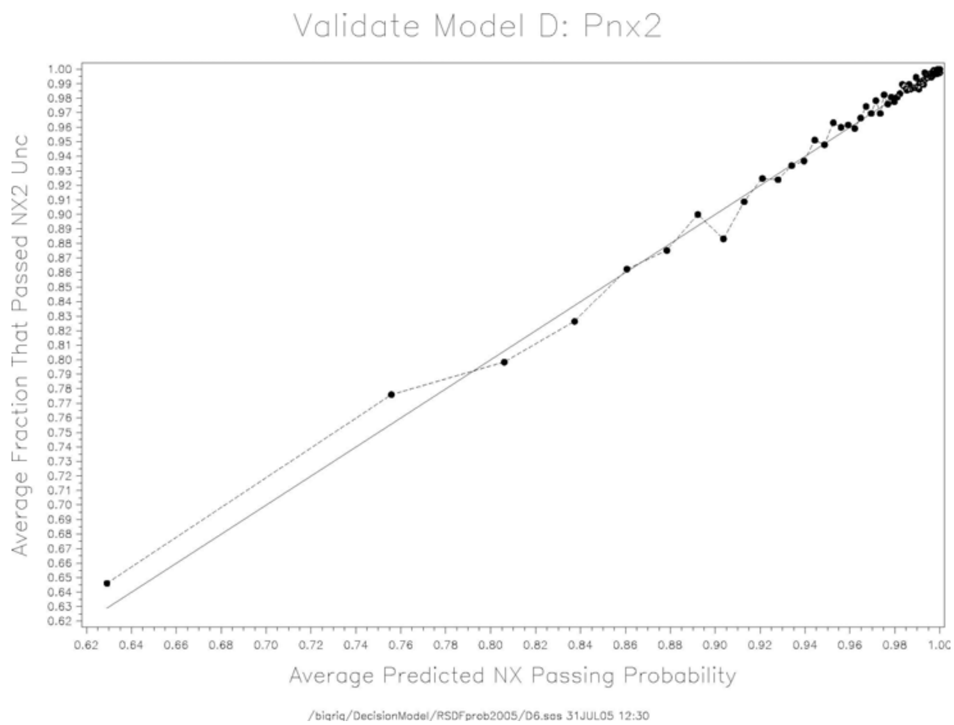


Figure D-12. Linearization Check for Equations D-13 and D-19 (Validation Dataset)

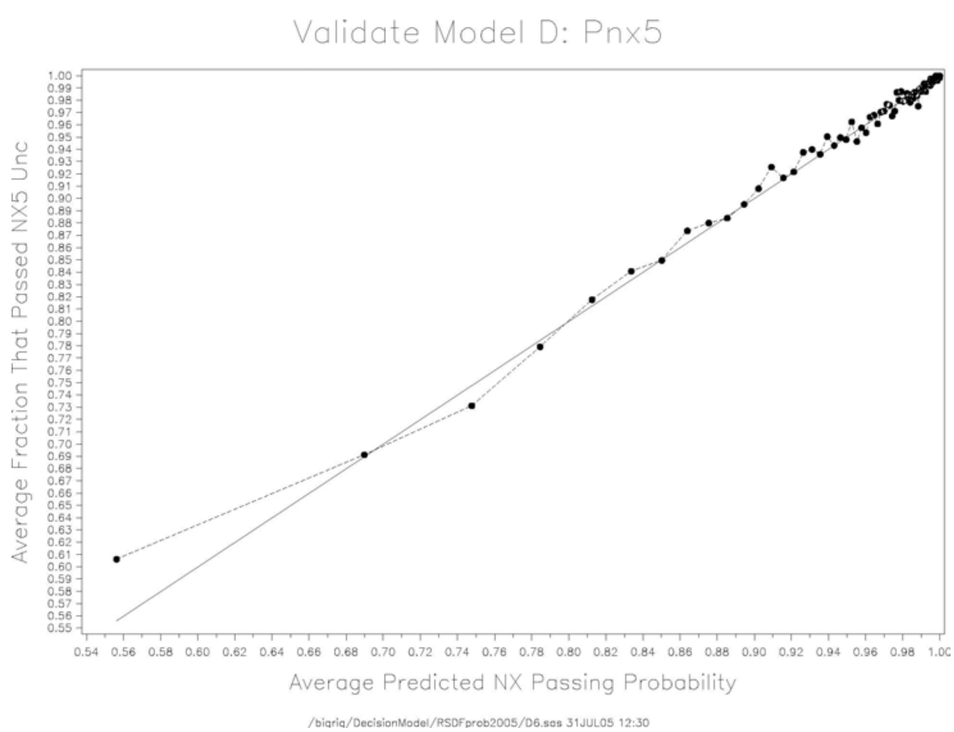


Figure D-13. Linearization Check for Equations D-2 and D-5 (Training Dataset)

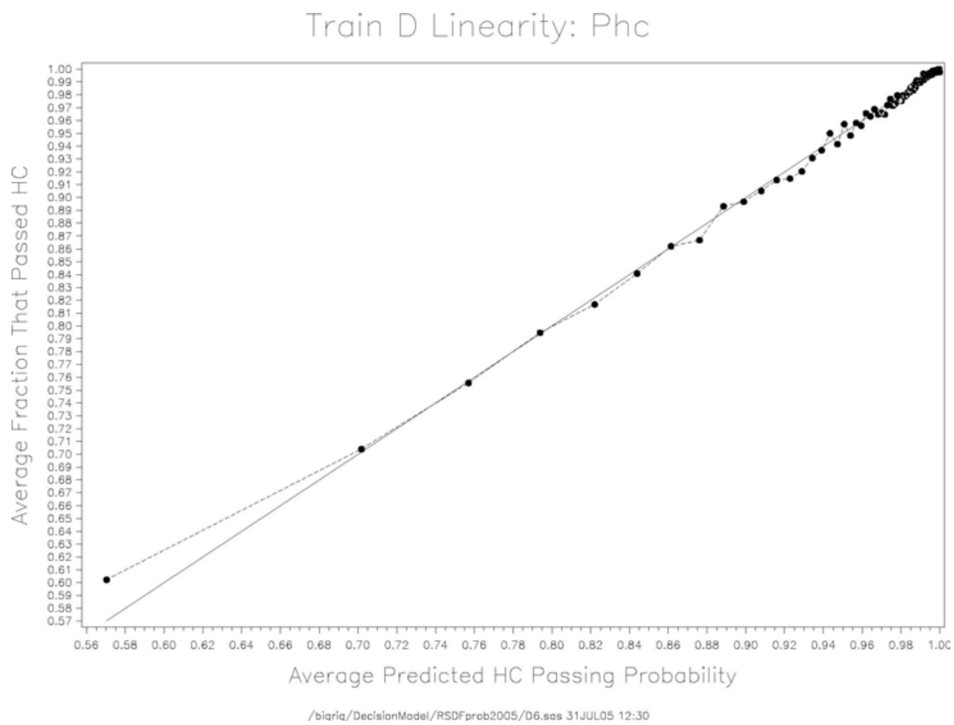


Figure D-14. Linearization Check for Equations D-3 and D-6 (Training Dataset)

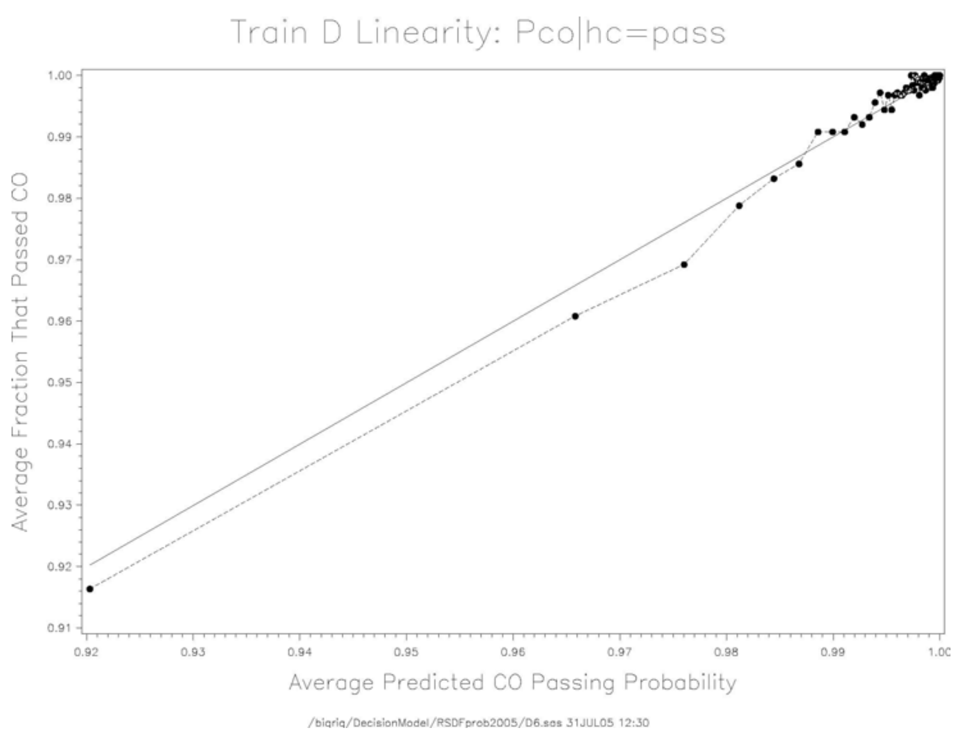


Figure D-15. Linearization Check for Equations D-4 and D-7 (Training Dataset)

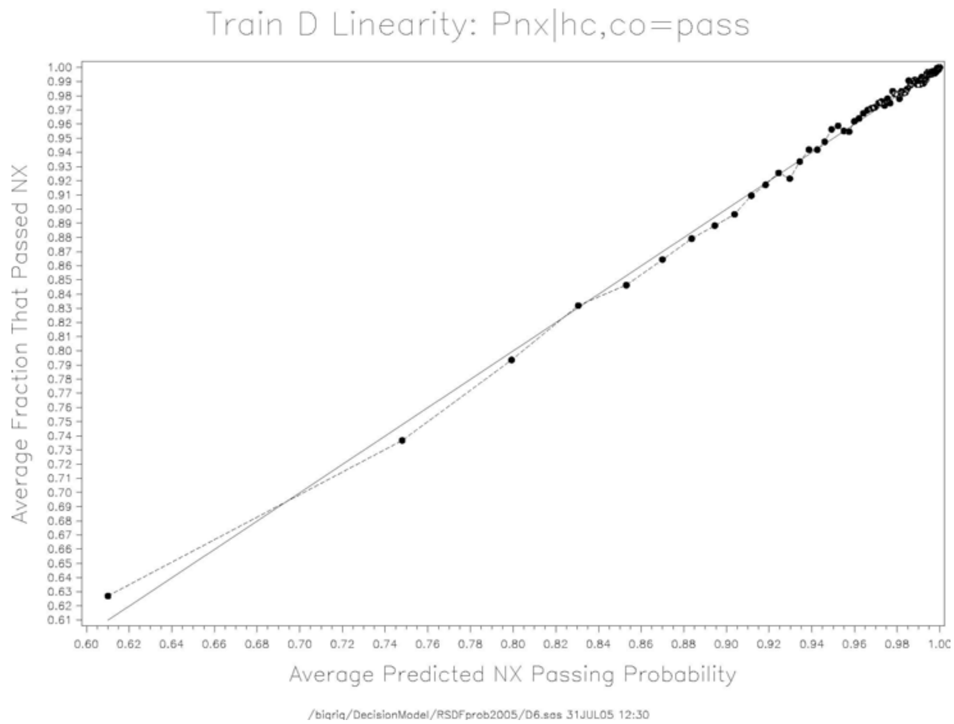


Figure D-16. Linearization Check for Equations D-1 (Training Dataset)

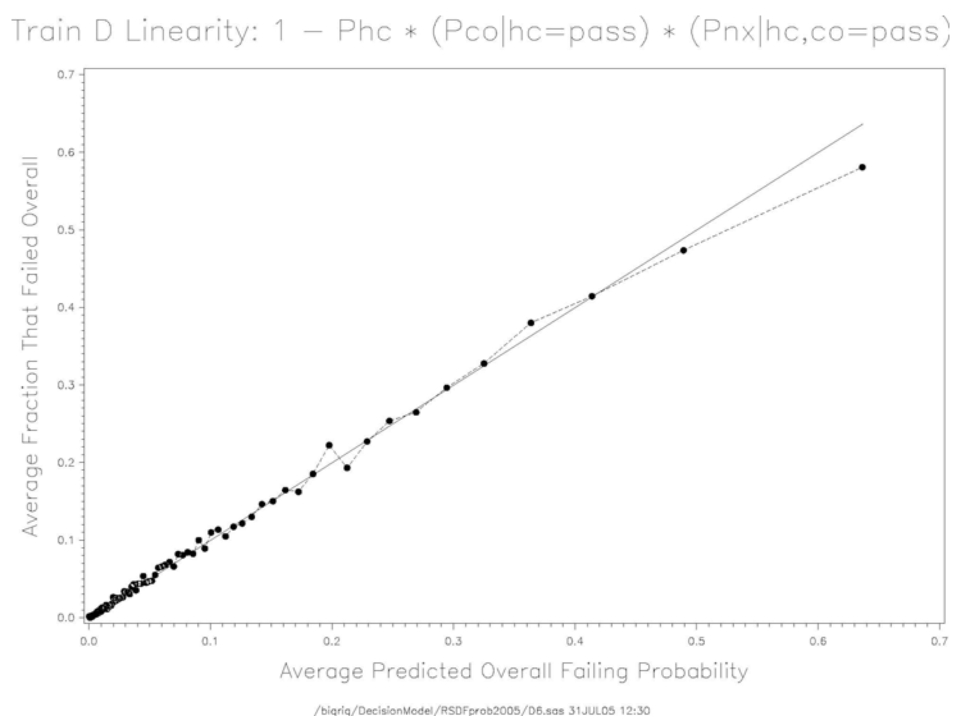


Figure D-17. Linearization Check for Equations D-2 and D-5 (Validation Dataset)

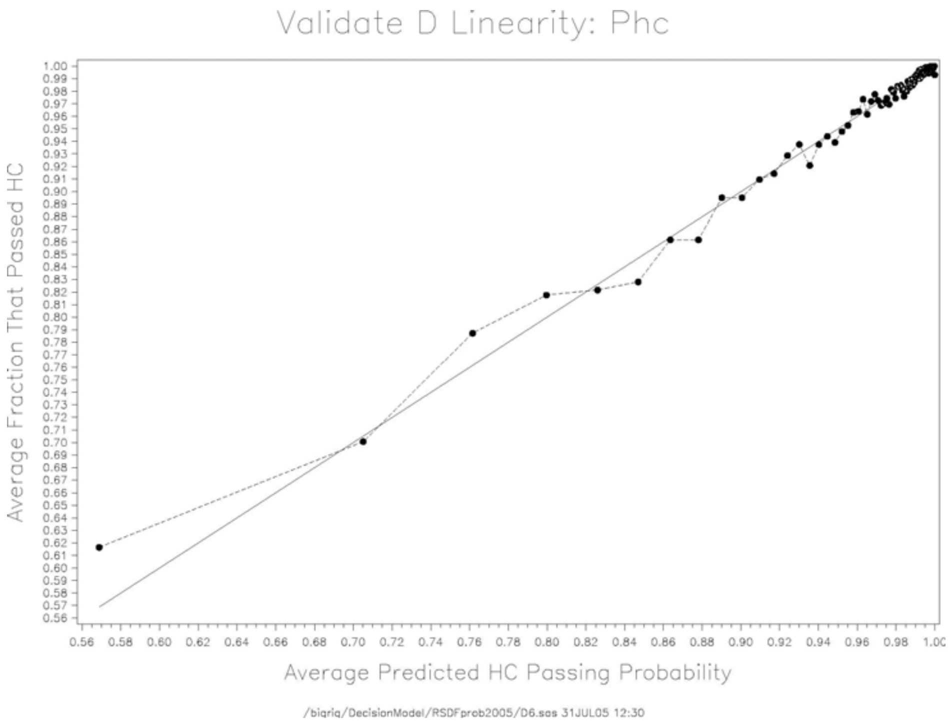


Figure D-18. Linearization Check for Equations D-3 and D-6 (Validation Dataset)

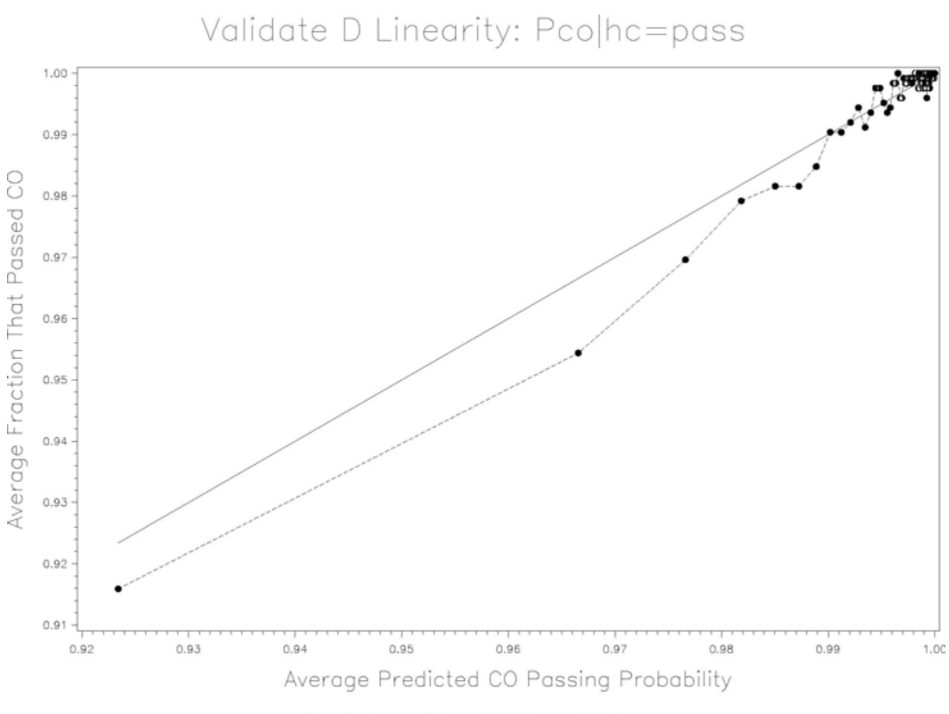


Figure D-19. Linearization Check for Equations D-4 and D-7 (Validation Dataset)

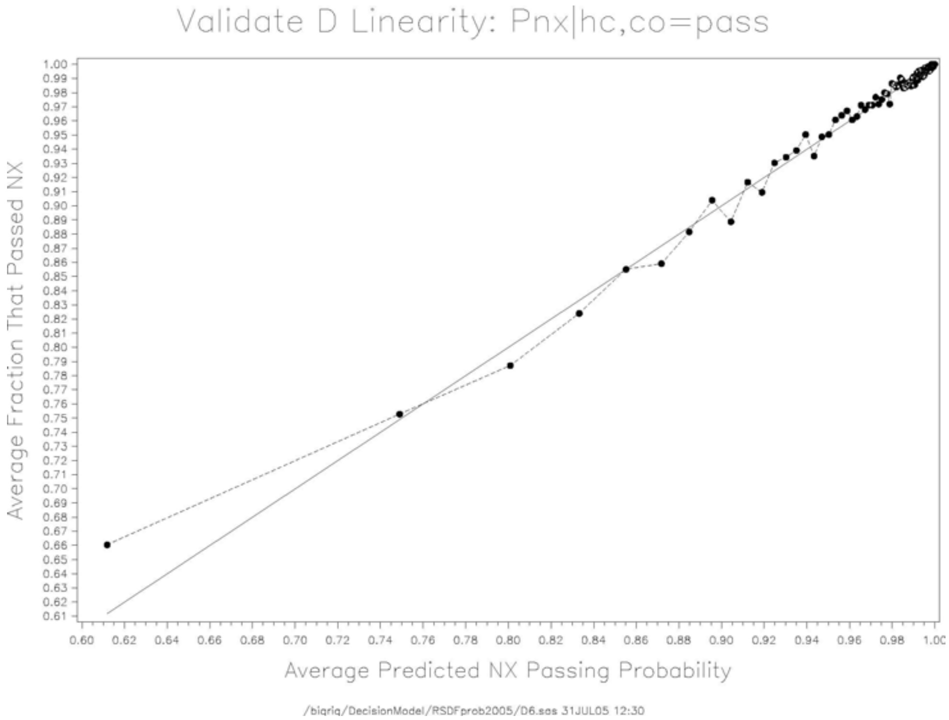
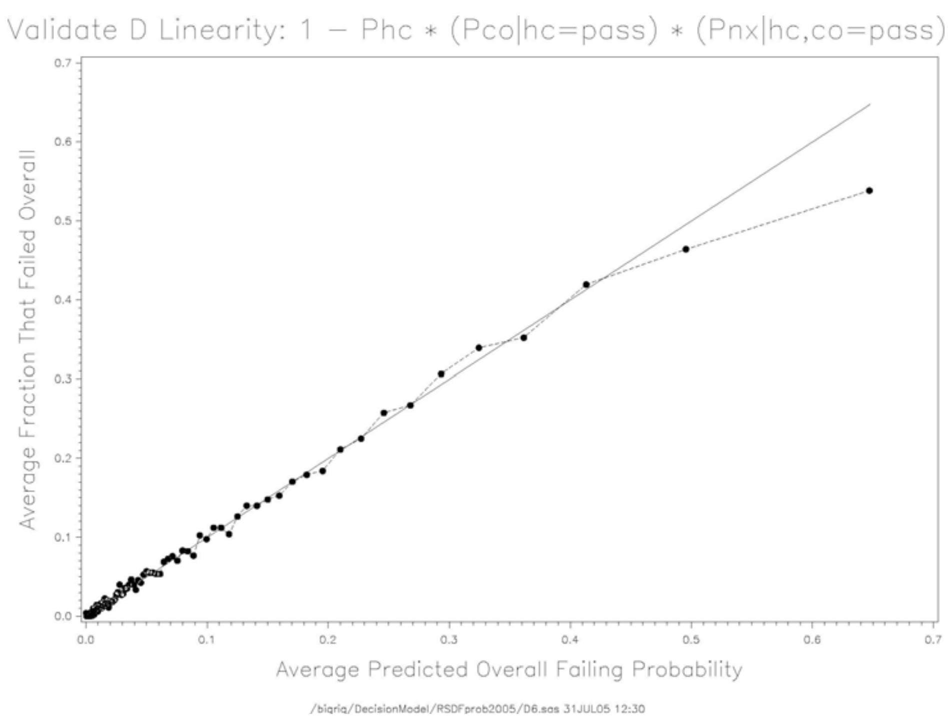


Figure D-20. Linearization Check for Equations D-1 (Validation Dataset)



Appendix E

Model E ASM Failure Probability Equations

One of the limitations of Model F is the lack of ASM cutpoint dependence. The Model E equations, which are described in this section, add the six ASM mode/pollutant cutpoints to the RSD measurements for the purposes of estimating ASM failure probabilities.

One of the inherent problems with using RSD measurements to identify vehicles that would fail an I/M test is that different vehicles have different I/M cutpoints. It makes sense that I/M cutpoints should have an influence on the ability of RSD measurements to properly select vehicles that would fail the I/M test. This can be demonstrated with a simple example. Suppose there were two vehicles that had the same RSD measurement values. If we wanted to select vehicles that we thought would fail the I/M test based only on the RSD values, both vehicles would be selected at the same time. However, if one vehicle had lower I/M cutpoints than the other vehicle, the vehicle with the lower I/M cutpoints would be more likely to fail the I/M test.

For Model E, we developed equations to predict the overall ASM failing probability as a function of:

- RSD HC (ppm);
- RSD CO (%);
- RSD NX (ppm);
- ASM 2525 HC (ppm);
- ASM 5015 HC (ppm);
- ASM 2525 CO (%);
- ASM 5015 CO (%);
- ASM 2525 NX (ppm);
- ASM 5015 NX (ppm).

In addition, because Model E will contain ASM cutpoint functionality it will become possible to use the model equations to estimate expected ASM mode/pollutant concentrations for individual vehicles which can thereby be used to estimate FTP emission rates.

The first step in the development of the Model E equations is performing regressions that can predict the ASM mode/pollutant passing probabilities. The results are given by Equations E-14 through E-22. Each of these equations contains functionalities for the RSD HC, CO, and NX measurements and the individual ASM mode/pollutant cutpoints as given in Equations E-23 through E-31. The RSD measurements were linearized using the relationships given in Equations G-2, G-7, and G-10. The natural log of the appropriate ASM mode/pollutant cutpoint was used as an input to each of these equations to provide cutpoint functionality.

The datasets on which the ASM mode/pollutant models were built were created by making two special manipulations. First, if the ASM mode/pollutant model to be built was a conditional model, for example, the passing probability of ASM 5015 hydrocarbon given that the ASM 2525 hydrocarbon was a pass, the dataset used to build the model contain only observations where ASM 2525 hydrocarbon was a pass. If the model was not conditional, for example, for the passing probability of ASM 2525 CO, then all observations were used. Second, to provide the observations over a range of ASM mode/pollutant cutpoints each dataset created for a mode/pollutant regression was replicated five times using different values for cutpoints to determine the fail and pass status of each mode/pollutant test. One of the replicates used the original I/M ASM mode/pollutant cutpoint. Four other replicates were created using values of the same ASM mode/pollutant quantity that were higher than the original cutpoint value. These quantities were selected to be the 20, 40, 60 and 80 percentile values of the observations in the dataset that failed the ASM mode/pollutant under investigation.

The SAS logistic regression procedure was used to build each of the nine ASM mode/pollutant models. The best models were found by using automated stepwise regression as well as manual examination of regression results. The coefficients for the final ASM mode/pollutant regressions are given in Equations E-23 through E-31. Table E-1 gives the number of observations used to build the models. Note that the number of observations are five times larger than the original dataset because of the cutpoint replication method used to find the cutpoint dependence. The concordances for all of the models are relatively high. Seven of the nine ASM mode/pollutant models have significant lack of fit; however, an examination of the linearity plots in Figures E-1 through E-9 shows that the lack of fit is of small practical importance.

Table E-1.

Model Equation	Model Response	Obs			Concordance (%)	Goodness of Fit Pr
		Pass	Fail	Total		
E-2 / E-5	P_{HC}	283148	8910	292058	83.8	0.0804
E-3 / E-6	P_{CO} | HC Pass	282254	894	283148	76.9	0.0017
E-4 / E-7	P_{NX} | HC,CO Pass	274463	7791	282254	82.1	0.0001
E-14 / E-23	P_{HC2}	285214	6844	292058	85.0	0.0001
E-15 / E-24	P_{HC5}	284895	7163	292058	83.4	0.0001
E-16 / E-25	P_{HC5} | HC2 Pass	283148	2066	285214	74.0	0.0737
E-17 / E-26	P_{CO2}	288698	3360	292058	84.1	0.5233
E-18 / E-27	P_{CO5}	288432	3626	292058	83.5	0.0011
E-19 / E-28	P_{CO5} | CO2 Pass	287811	887	288698	74.2	0.0097
E-20 / E-29	P_{NX2}	285266	6792	292058	86.1	0.0001
E-21 / E-30	P_{NX5}	282091	9967	292058	83.7	0.0001
E-22 / E-31	P_{NX5} | NX2 Pass	281005	4261	285266	79.6	0.0003

Equations E-14, E-15, E-17, E-18, E-20, and E-21 can be integrated as described elsewhere in this report to estimate the expected ASM mode/pollutant emissions for individual vehicles. Equations E-14, E-16, E-17, E-19, E-20, and E-22 can be combined as described in Equations E-11, E-12, and E-13 to provide estimates of ASM pollutant failure probabilities.

A final set of regressions is used to combine the ASM pollutant failure probabilities F_{HC}, F_{CO}, and F_{NX}. The first step in this process is to calculate the logit of these three failure probabilities as described in Equations E-8, E-9, and E-10 for all of the observations in the training dataset as calculated by using the models that have been developed so far. The next step was to use logistic regression to determine coefficients for Equations E-5, E-6, and E-7. The regressions were performed on the replicated dataset which was subsetted, if necessary, to meet the conditional requirements as expressed in Equations E-2, E-3, and E-4. Coefficients were determined and found to be significant for the main effect and two-factor interactions of the logit of the three ASM pollutant probabilities. The coefficients are given in Equations E-5, E-6, and E-7. Figures E-25, E-26, and E-27 show the linearity of these three models.

The following Model E equations can be used to calculate the overall ASM failure probability of a vehicle based on measured RSD emissions concentrations and ASM cutpoints. None of the coefficients in these equations are vehicle-specific. Equations E-14, 15, 17, 18, 20, and 21 can be used with calculus to estimate average ASM emissions and with ASM-to-FTP relationships to estimate average FTP emissions.

$$F_{Overall\ Model\ E} = 1 - (P_{HC}) * (P_{CO} \mid HC\ Pass) * (P_{NX} \mid HC,CO\ Pass) \quad [E\text{-}1]$$

where:

$$P_{HC} = \exp(arg3\_HCunc) / (1 + \exp(arg3\_HCunc)) \quad [E\text{-}2]$$

$$P_{CO} \mid HC\ Pass = \exp(arg3\_COcon) / (1 + \exp(arg3\_COcon)) \quad [E\text{-}3]$$

$$P_{NX} \mid HC,CO\ Pass = \exp(arg3\_NXcon) / (1 + \exp(arg3\_NXcon)) \quad [E\text{-}4]$$

where:

$$\begin{aligned} arg3\_HCunc = & - 0.20652 \\ & - 0.59933 * logit\_F_{HC} \\ & - 0.08405 * logit\_F_{CO} \\ & - 0.26292 * logit\_F_{NX} \\ & + 0.05878 * logit\_F_{HC} * logit\_F_{CO} \\ & - 0.15234 * logit\_F_{HC} * logit\_F_{NX} \\ & + 0.08608 * logit\_F_{CO} * logit\_F_{NX} \end{aligned} \quad [E\text{-}5]$$

$$\begin{aligned} arg3\_COcon = & + 2.06430 \\ & + 2.47535 * logit\_F_{HC} \\ & - 1.76510 * logit\_F_{CO} \\ & - 0.86509 * logit\_F_{NX} \\ & + 0.38763 * logit\_F_{HC} * logit\_F_{CO} \\ & + 0.00000 * logit\_F_{HC} * logit\_F_{NX} \\ & - 0.28927 * logit\_F_{CO} * logit\_F_{NX} \end{aligned} \quad [E\text{-}6]$$

$$\begin{aligned} arg3\_NXcon = & + 0.74616 \\ & + 0.71014 * logit\_F_{HC} \\ & - 0.28626 * logit\_F_{CO} \\ & - 0.96481 * logit\_F_{NX} \\ & + 0.04792 * logit\_F_{HC} * logit\_F_{CO} \\ & + 0.00000 * logit\_F_{HC} * logit\_F_{NX} \\ & + 0.00000 * logit\_F_{CO} * logit\_F_{NX} \end{aligned} \quad [E\text{-}7]$$

where:

$$logit\_F_{HC} = \ln(F_{HC} / (1-F_{HC})) \quad [E\text{-}8]$$

$$logit\_F_{CO} = \ln(F_{CO} / (1-F_{CO})) \quad [E\text{-}9]$$

$$logit\_F_{NX} = \ln(F_{NX} / (1-F_{NX})) \quad [E\text{-}10]$$

where:

$$F_{HC} = 1 - (P_{HC2}) * (P_{HC5} \mid HC2\ Pass) \quad [E\text{-}11]$$

$$F_{CO} = 1 - (P_{CO2}) * (P_{CO5} \mid CO2\ Pass) \quad [E\text{-}12]$$

$$F_{NX} = 1 - (P_{NX2}) * (P_{NX5} \mid NX2\ Pass) \quad [E\text{-}13]$$

where:

P_{HC2} = exp(arg2_HC2unc) / (1 + exp(arg2_HC2unc)) [E-14]
P_{HC5} = exp(arg2_HC5unc) / (1 + exp(arg2_HC5unc)) [E-15]
P_{HC5} | HC2 Pass = exp(arg2_HC5con) / (1 + exp(arg2_HC5con)) [E-16]
P_{CO2} = exp(arg2_CO2unc) / (1 + exp(arg2_CO2unc)) [E-17]
P_{CO5} = exp(arg2_CO5unc) / (1 + exp(arg2_CO5unc)) [E-18]
P_{CO5} | CO2 Pass = exp(arg2_CO5con) / (1 + exp(arg2_CO5con)) [E-19]
P_{NX2} = exp(arg2_NX2unc) / (1 + exp(arg2_NX2unc)) [E-20]
P_{NX5} = exp(arg2_NX5unc) / (1 + exp(arg2_NX5unc)) [E-21]
P_{NX5} | NX2 Pass = exp(arg2_NX5con) / (1 + exp(arg2_NX5con)) [E-22]

where:

arg2_HC2unc = – 3.7389 [E-23]
+ 0.67635 * logHC_2x
+ 0.66852 * arg_tRSDHC
+ 0.29848 * arg_tRSDCO
+ 0.17846 * arg_tRSDNX
+ 0.00000 * arg_tRSDHC * arg_tRSDCO
+ 0.00000 * arg_tRSDHC * arg_tRSDNX
+ 0.08417 * arg_tRSDCO * arg_tRSDNX

arg2_HC5unc = – 3.2217 [E-24]
+ 0.57560 * logHC_5x
+ 0.63500 * arg_tRSDHC
+ 0.24464 * arg_tRSDCO
+ 0.18748 * arg_tRSDNX
+ 0.00000 * arg_tRSDHC * arg_tRSDCO
+ 0.00000 * arg_tRSDHC * arg_tRSDNX
+ 0.07997 * arg_tRSDCO * arg_tRSDNX

arg2_HC5con = + 0.1515 [E-25]
+ 0.35719 * logHC_5x
+ 0.43107 * arg_tRSDHC
+ 0.07768 * arg_tRSDCO
+ 0.18621 * arg_tRSDNX
+ 0.00000 * arg_tRSDHC * arg_tRSDCO
+ 0.00000 * arg_tRSDHC * arg_tRSDNX
+ 0.07316 * arg_tRSDCO * arg_tRSDNX

arg2_CO2unc = – 0.2760 [E-26]
+ 0.50245 * logCO_2x
+ 0.84445 * arg_tRSDHC
+ 0.81162 * arg_tRSDCO
– 0.17039 * arg_tRSDNX
– 0.16035 * arg_tRSDHC * arg_tRSDCO
+ 0.00000 * arg_tRSDHC * arg_tRSDNX
+ 0.14570 * arg_tRSDCO * arg_tRSDNX

$$
\begin{aligned}
\text{arg2\_CO5unc} = {} & -0.3895 \\
& + 0.41588 * \text{logCO\_5x} \\
& + 0.86541 * \text{arg\_tRSDHC} \\
& + 0.77257 * \text{arg\_tRSDCO} \\
& - 0.10111 * \text{arg\_tRSDNX} \\
& - 0.15802 * \text{arg\_tRSDHC} * \text{arg\_tRSDCO} \\
& + 0.00000 * \text{arg\_tRSDHC} * \text{arg\_tRSDNX} \\
& + 0.13893 * \text{arg\_tRSDCO} * \text{arg\_tRSDNX}
\end{aligned} \tag{E-27}
$$

$$
\begin{aligned}
\text{arg2\_CO5con} = {} & + 1.7169 \\
& + 0.61487 * \text{logCO\_5x} \\
& + 0.53992 * \text{arg\_tRSDHC} \\
& + 0.33967 * \text{arg\_tRSDCO} \\
& + 0.15855 * \text{arg\_tRSDNX} \\
& + 0.00000 * \text{arg\_tRSDHC} * \text{arg\_tRSDCO} \\
& + 0.00000 * \text{arg\_tRSDHC} * \text{arg\_tRSDNX} \\
& + 0.10892 * \text{arg\_tRSDCO} * \text{arg\_tRSDNX}
\end{aligned} \tag{E-28}
$$

$$
\begin{aligned}
\text{arg2\_NX2unc} = {} & - 11.4527 \\
& + 1.62338 * \text{logNX\_2x} \\
& - 0.20142 * \text{arg\_tRSDHC} \\
& + 0.16950 * \text{arg\_tRSDCO} \\
& + 0.90156 * \text{arg\_tRSDNX} \\
& + 0.09319 * \text{arg\_tRSDHC} * \text{arg\_tRSDCO} \\
& + 0.048042 * \text{arg\_tRSDHC} * \text{arg\_tRSDNX} \\
& + 0.00000 * \text{arg\_tRSDCO} * \text{arg\_tRSDNX}
\end{aligned} \tag{E-29}
$$

$$
\begin{aligned}
\text{arg2\_NX5unc} = {} & - 7.4366 \\
& + 1.04028 * \text{logNX\_5x} \\
& - 0.25262 * \text{arg\_tRSDHC} \\
& + 0.14409 * \text{arg\_tRSDCO} \\
& + 0.84409 * \text{arg\_tRSDNX} \\
& + 0.10169 * \text{arg\_tRSDHC} * \text{arg\_tRSDCO} \\
& + 0.038850 * \text{arg\_tRSDHC} * \text{arg\_tRSDNX} \\
& + 0.00000 * \text{arg\_tRSDCO} * \text{arg\_tRSDNX}
\end{aligned} \tag{E-30}
$$

$$
\begin{aligned}
\text{arg2\_NX5con} = {} & - 8.1634 \\
& + 1.43819 * \text{logNX\_5x} \\
& - 0.49390 * \text{arg\_tRSDHC} \\
& + 0.11005 * \text{arg\_tRSDCO} \\
& + 0.51675 * \text{arg\_tRSDNX} \\
& + 0.10445 * \text{arg\_tRSDHC} * \text{arg\_tRSDCO} \\
& + 0.093458 * \text{arg\_tRSDHC} * \text{arg\_tRSDNX} \\
& + 0.00000 * \text{arg\_tRSDCO} * \text{arg\_tRSDNX}
\end{aligned} \tag{E-31}
$$

where:

P_{NX} | HC,CO Pass — denotes the fractional conditional Passing probability of ASM NX (that is, both ASM2525 NX and ASM5015 NX pass) given that ASM HC (both modes) and ASM CO (both modes) have already passed.

F_{HC} — denotes the fractional unconditional Failing probability of ASM HC (that is, either ASM2525 HC or ASM5015 HC fail or both).

P_{NX5} | NX2 Pass — denotes the fractional conditional Passing probability of ASM5015 NX given that ASM2525 NX has already passed.

logHC_2x = ln (ASM2525 HC cutpoint (ppm))
logHC_5x = ln (ASM5015 HC cutpoint (ppm))
logCO_2x = ln (ASM2525 CO cutpoint (%))
logCO_5x = ln (ASM5015 CO cutpoint (%))
logNX_2x = ln (ASM2525 NX cutpoint (ppm))
logNX_5x = ln (ASM5015 NX cutpoint (ppm))

arg_tRSDHC is calculated by Equation G-2
arg_tRSDCO is calculated by Equation G-7
arg_tRSDNX is calculated by Equation G-10

Table E-1. SAS Output for Equations E-14 and E-23

```
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                                  The LOGISTIC Procedure

                                    Model Information

                       Data Set                      WORK.HC2UNC
                       Response Variable             tr_hc2res_pass
                       Number of Response Levels     2
                       Number of Observations        292058
                       Link Function                 Logit
                       Optimization Technique        Fisher's scoring


                                     Response Profile

                            Ordered     tr_hc2res_         Total
                              Value     pass           Frequency

                                  1           1           285214
                                  2           0             6844

NOTE: 143067 observations were deleted due to missing values for the response or explanatory variables.


                                 Model Convergence Status

                       Convergence criterion (GCONV=1E-8) satisfied.


                                  Model Fit Statistics

                                                         Intercept
                                          Intercept         and
                          Criterion         Only        Covariates

                          AIC             64907.356      50785.733
                          SC              64917.941      50849.241
                          -2 Log L        64905.356      50773.733




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                                  The LOGISTIC Procedure

                          Testing Global Null Hypothesis: BETA=0

                     Test                 Chi-Square       DF     Pr > ChiSq

                     Likelihood Ratio     14131.6229        5         <.0001
                     Score                19169.3784        5         <.0001
                     Wald                 11113.9194        5         <.0001


                          Analysis of Maximum Likelihood Estimates

                                                     Standard
            Parameter              DF     Estimate      Error     Chi-Square    Pr > ChiSq

            Intercept               1      -3.7389     0.1536       592.7110        <.0001
            loghc_2x                1       0.6763     0.0251       728.3159        <.0001
            arg_tRSDHC              1       0.6685     0.0159      1763.3736        <.0001
            arg_tRSDCO              1       0.2985     0.0286       108.9492        <.0001
            arg_tRSDNX              1       0.1785     0.0321        30.9758        <.0001
            arg_tRSDC*arg_tRSDNX    1       0.0842    0.00915        84.6034        <.0001


                                   Odds Ratio Estimates

                                        Point          95% Wald
                       Effect        Estimate      Confidence Limits

                       loghc_2x         1.967       1.872       2.066
                       arg_tRSDHC       1.951       1.891       2.013


                  Association of Predicted Probabilities and Observed Responses

                   Percent Concordant         85.0    Somers' D    0.718
                   Percent Discordant         13.2    Gamma        0.731
                   Percent Tied                1.8    Tau-a        0.033
                   Pairs                1952004616    c            0.859



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```

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

		tr_hc2res_pass = 1		tr_hc2res_pass = 0	
Group	Total	Observed	Expected	Observed	Expected
1	29207	25124	25196.24	4083	4010.76
2	29195	28035	28012.30	1160	1182.70
3	29280	28755	28690.39	525	589.61
4	28816	28477	28458.74	339	357.26
5	29361	29135	29116.09	226	244.91
6	28845	28678	28676.32	167	168.68
7	29273	29153	29150.98	120	122.02
8	28601	28520	28515.54	81	85.46
9	27812	27745	27753.59	67	58.41
10	31668	31592	31629.33	76	38.67

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
49.2227	8	<.0001

Table E-2 SAS Output for Equations E-15 and E-24

The LOGISTIC Procedure

Model Information

Data Set	WORK.HC5UNC
Response Variable	tr_hc5res_pass
Number of Response Levels	2
Number of Observations	292058
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	tr_hc5res_pass	Total Frequency
1	1	284895
2	0	7163

NOTE: 143067 observations were deleted due to missing values for the response or explanatory variables.

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	67272.012	53996.926
SC	67282.596	54060.434
-2 Log L	67270.012	53984.926

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	13285.0856	5	<.0001
Score	17964.3576	5	<.0001
Wald	10794.0016	5	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	-3.2217	0.1761	334.6341	<.0001
loghc_5x	1	0.5756	0.0297	374.5025	<.0001
arg_tRSDHC	1	0.6350	0.0153	1721.0247	<.0001
arg_tRSDCO	1	0.2446	0.0275	79.2859	<.0001
arg_tRSDNX	1	0.1875	0.0316	35.2319	<.0001
arg_tRSDC*arg_tRSDNX	1	0.0800	0.00881	82.4028	<.0001

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
loghc_5x	1.778	1.677	1.885
arg_tRSDHC	1.887	1.831	1.944

Association of Predicted Probabilities and Observed Responses

Percent Concordant	83.4	Somers' D	0.686
Percent Discordant	14.8	Gamma	0.699
Percent Tied	1.9	Tau-a	0.033
Pairs	2040702885	c	0.843

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

Group	Total	tr_hc5res_pass = 1 Observed	tr_hc5res_pass = 1 Expected	tr_hc5res_pass = 0 Observed	tr_hc5res_pass = 0 Expected
1	29221	25200	25254.72	4021	3966.28
2	29193	27960	27918.70	1233	1274.30
3	29382	28773	28721.35	609	660.65
4	29318	28933	28903.27	385	414.73
5	29027	28738	28745.07	289	281.93
6	29943	29735	29736.07	208	206.93
7	29603	29471	29455.53	132	147.47
8	30205	30100	30096.22	105	108.78
9	30435	30335	30358.20	100	76.80
10	25731	25650	25691.40	81	39.60

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
60.8869	8	<.0001

Table E-3. SAS Output for Equations E-16 and E-25

The LOGISTIC Procedure

Model Information

Data Set	WORK.HC5COND
Response Variable	tr_hc5res_pass
Number of Response Levels	2
Number of Observations	285214
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	tr_hc5res_ pass	Total Frequency
1	1	283148
2	0	2066

NOTE: 149911 observations were deleted due to missing values for the response or explanatory variables.

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	24479.946	22287.579
SC	24490.507	22350.945
-2 Log L	24477.946	22275.579

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	2202.3676	5	<.0001
Score	2795.9084	5	<.0001
Wald	2061.1836	5	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	0.1515	0.3153	0.2309	0.6309
loghc_5x	1	0.3572	0.0518	47.5822	<.0001
arg_tRSDHC	1	0.4311	0.0260	274.5489	<.0001
arg_tRSDCO	1	0.0777	0.0487	2.5435	0.1107
arg_tRSDNX	1	0.1862	0.0613	9.2282	0.0024
arg_tRSDC*arg_tRSDNX	1	0.0732	0.0155	22.2830	<.0001

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
loghc_5x	1.429	1.291	1.582
arg_tRSDHC	1.539	1.462	1.619

Association of Predicted Probabilities and Observed Responses

Percent Concordant	74.0	Somers' D	0.549
Percent Discordant	19.1	Gamma	0.590
Percent Tied	6.9	Tau-a	0.008
Pairs	584983768	c	0.775

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

		tr_hc5res_pass = 1		tr_hc5res_pass = 0	
Group	Total	Observed	Expected	Observed	Expected
1	28547	27689	27688.77	858	858.23
2	28244	27868	27869.64	376	374.36
3	28688	28438	28445.79	250	242.21
4	28888	28705	28715.63	183	172.37
5	27183	27055	27061.82	128	121.18
6	28910	28831	28811.07	79	98.93
7	30829	30772	30748.02	57	80.98
8	28325	28267	28267.38	58	57.62
9	25868	25831	25826.77	37	41.23
10	29732	29692	29698.88	40	33.12

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
14.3223	8	0.0737

Table E-4. SAS Output for Equations E-17 and E-26

The LOGISTIC Procedure

Model Information

Data Set	WORK.CO2UNC
Response Variable	tr_co2res_pass
Number of Response Levels	2
Number of Observations	292058
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	tr_co2res_ pass	Total Frequency
1	1	288698
2	0	3360

NOTE: 143067 observations were deleted due to missing values for the response or explanatory variables.

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	36688.072	28892.702
SC	36698.657	28966.795
-2 Log L	36686.072	28878.702

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	7807.3706	6	<.0001
Score	14850.2085	6	<.0001
Wald	7010.9243	6	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	-0.2760	0.1439	3.6776	0.0551
logco_2x	1	0.5024	0.0256	384.6319	<.0001
arg_tRSDHC	1	0.8445	0.0484	304.3776	<.0001
arg_tRSDCO	1	0.8116	0.0499	264.7044	<.0001
arg_tRSDNX	1	-0.1704	0.0404	17.7626	<.0001
arg_tRSDC*arg_tRSDNX	1	0.1457	0.0124	137.1342	<.0001
arg_tRSDH*arg_tRSDCO	1	-0.1603	0.0133	144.7458	<.0001

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
logco_2x	1.653	1.572	1.738

Association of Predicted Probabilities and Observed Responses

Percent Concordant	84.1	Somers' D	0.718
Percent Discordant	12.2	Gamma	0.746
Percent Tied	3.7	Tau-a	0.016
Pairs	970025280	c	0.859

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

Group	Total	tr_co2res_pass = 1 Observed	tr_co2res_pass = 1 Expected	tr_co2res_pass = 0 Observed	tr_co2res_pass = 0 Expected
1	29198	27156	27112.52	2042	2085.48
2	29080	28581	28601.34	499	478.66
3	29428	29156	29159.56	272	268.44
4	29309	29116	29133.27	193	175.73
5	30112	29988	29987.47	124	124.53
6	29994	29913	29906.71	81	87.29
7	31143	31084	31078.55	59	64.45
8	30546	30508	30500.81	38	45.19
9	27847	27815	27818.08	32	28.92
10	25401	25381	25385.21	20	15.79

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
7.1237	8	0.5233

Table E-5. SAS Output for Equations E-18 and E-27

The LOGISTIC Procedure

Model Information

Data Set	WORK.CO5UNC
Response Variable	tr_co5res_pass
Number of Response Levels	2
Number of Observations	292058
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	tr_co5res_pass	Total Frequency
1	1	288432
2	0	3626

NOTE: 143067 observations were deleted due to missing values for the response or explanatory variables.

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	39036.534	31126.207
SC	39047.119	31200.300
-2 Log L	39034.534	31112.207

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	7922.3273	6	<.0001
Score	14703.0617	6	<.0001
Wald	7088.2925	6	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	-0.3895	0.1393	7.8178	0.0052
logco_5x	1	0.4159	0.0251	273.5126	<.0001
arg_tRSDHC	1	0.8654	0.0476	330.5042	<.0001
arg_tRSDCO	1	0.7726	0.0473	266.2499	<.0001
arg_tRSDNX	1	-0.1011	0.0393	6.6131	0.0101
arg_tRSDC*arg_tRSDNX	1	0.1389	0.0119	136.6291	<.0001
arg_tRSDH*arg_tRSDCO	1	-0.1580	0.0129	151.0794	<.0001

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
logco_5x	1.516	1.443	1.592

Association of Predicted Probabilities and Observed Responses

Percent Concordant	83.5	Somers' D	0.706
Percent Discordant	13.0	Gamma	0.731
Percent Tied	3.5	Tau-a	0.017
Pairs	1045854432	c	0.853

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

Group	Total	tr_co5res_pass = 1 Observed	tr_co5res_pass = 1 Expected	tr_co5res_pass = 0 Observed	tr_co5res_pass = 0 Expected
1	29176	27030	26982.10	2146	2193.90
2	29030	28462	28499.74	568	530.26
3	29097	28802	28799.25	295	297.75
4	28533	28350	28338.27	183	194.73
5	29738	29590	29596.36	148	141.64
6	28438	28350	28341.60	88	96.40
7	29676	29602	29603.30	74	72.70
8	31761	31709	31705.23	52	55.77
9	32141	32106	32101.82	35	39.18
10	24468	24431	24449.84	37	18.16

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
25.9015	8	0.0011

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Table E-6. SAS Output for Equations E-19 and E-28

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The LOGISTIC Procedure

Model Information

Data Set	WORK.CO5COND
Response Variable	tr_co5res_pass
Number of Response Levels	2
Number of Observations	288698
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	tr_co5res_pass	Total Frequency
1	1	287811
2	0	887

NOTE: 146427 observations were deleted due to missing values for the response or explanatory variables.

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	12036.379	10476.107
SC	12046.952	10560.693
-2 Log L	12034.379	10460.107

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The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	1574.2716	7	<.0001
Score	2400.1530	7	<.0001
Wald	1349.3363	7	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	1.7169	0.2931	34.3211	<.0001
logco_5x	1	0.6149	0.0533	133.1305	<.0001
arg_tRSDHC	1	0.5399	0.1395	14.9711	0.0001
arg_tRSDCO	1	0.3397	0.0998	11.5816	0.0007
arg_tRSDNX	1	0.1586	0.0883	3.2273	0.0724
arg_tRSDC*arg_tRSDNX	1	0.1089	0.0318	11.7186	0.0006
arg_tRSDH*arg_tRSDCO	1	-0.0363	0.0267	1.8495	0.1738
arg_tRSDH*arg_tRSDNX	1	-0.0148	0.0343	0.1864	0.6659

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
logco_5x	1.849	1.666	2.053

Association of Predicted Probabilities and Observed Responses

Percent Concordant	74.2	Somers' D	0.627
Percent Discordant	11.5	Gamma	0.732
Percent Tied	14.3	Tau-a	0.004
Pairs	255288357	c	0.814

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

Group	Total	tr_co5res_pass = 1 Observed	tr_co5res_pass = 1 Expected	tr_co5res_pass = 0 Observed	tr_co5res_pass = 0 Expected
1	29056	28557	28572.98	499	483.02
2	28752	28623	28597.04	129	154.96
3	29979	29888	29888.38	91	90.62
4	30362	30315	30303.54	47	58.46
5	31355	31313	31314.43	42	40.57
6	29529	29502	29502.31	27	26.69
7	28207	28186	28188.44	21	18.56
8	38712	38696	38694.22	16	17.78
9	21111	21107	21104.41	4	6.59
10	21635	21624	21630.87	11	4.13

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
20.1635	8	0.0097

Table E-7. SAS Output for Equations E-20 and E-29

```
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                           The LOGISTIC Procedure

                             Model Information

               Data Set                      WORK.NX2UNC
               Response Variable             tr_nx2res_pass
               Number of Response Levels     2
               Number of Observations        292058
               Link Function                 Logit
               Optimization Technique        Fisher's scoring


                              Response Profile

                    Ordered     tr_nx2res_         Total
                      Value     pass           Frequency

                          1           1           285266
                          2           0             6792

NOTE: 143067 observations were deleted due to missing values for the response or explanatory variables.


                          Model Convergence Status

               Convergence criterion (GCONV=1E-8) satisfied.


                           Model Fit Statistics

                                             Intercept
                                Intercept          and
                  Criterion          Only   Covariates

                  AIC           64519.044    49756.637
                  SC            64529.629    49830.730
                  -2 Log L      64517.044    49742.637
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                           The LOGISTIC Procedure

                  Testing Global Null Hypothesis: BETA=0

          Test                 Chi-Square       DF     Pr > ChiSq

          Likelihood Ratio     14774.4069        6         <.0001
          Score                18944.3980        6         <.0001
          Wald                 10023.7392        6         <.0001


                  Analysis of Maximum Likelihood Estimates

                                             Standard
      Parameter              DF    Estimate     Error    Chi-Square    Pr > ChiSq

      Intercept               1    -11.4527    0.3648      985.5200        <.0001
      lognx_2x                1      1.6234    0.0487     1112.3147        <.0001
      arg_tRSDHC              1     -0.2014    0.0464       18.8847        <.0001
      arg_tRSDCO              1      0.1695    0.0290       34.1700        <.0001
      arg_tRSDNX              1      0.9016    0.0351      660.7818        <.0001
      arg_tRSDH*arg_tRSDCO    1      0.0932    0.0106       77.2322        <.0001
      arg_tRSDH*arg_tRSDNX    1      0.0480    0.0118       16.6891        <.0001


                            Odds Ratio Estimates

                              Point          95% Wald
               Effect      Estimate      Confidence Limits

               lognx_2x       5.070       4.609       5.578


         Association of Predicted Probabilities and Observed Responses

           Percent Concordant         86.1    Somers' D    0.740
           Percent Discordant         12.2    Gamma        0.752
           Percent Tied                1.7    Tau-a        0.034
           Pairs                1937526672    c            0.870
```

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```

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

		tr_nx2res_pass = 1		tr_nx2res_pass = 0	
Group	Total	Observed	Expected	Observed	Expected
1	29208	25150	25306.91	4058	3901.09
2	29133	27866	27796.65	1267	1336.35
3	29202	28629	28523.84	573	678.16
4	29038	28738	28666.67	300	371.33
5	28734	28548	28522.14	186	211.86
6	29148	29013	29019.74	135	128.26
7	27845	27751	27768.31	94	76.69
8	29743	29663	29690.11	80	52.89
9	31683	31616	31648.36	67	34.64
10	28324	28292	28308.68	32	15.32

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
111.4348	8	<.0001

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Table E-8 SAS Output for Equations E-21 and E-30

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The LOGISTIC Procedure

Model Information

Data Set	WORK.NX5UNC
Response Variable	tr_nx5res_pass
Number of Response Levels	2
Number of Observations	292058
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	tr_nx5res_ pass	Total Frequency
1	1	282091
2	0	9967

NOTE: 143067 observations were deleted due to missing values for the response or explanatory variables.

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	86922.451	69513.833
SC	86933.035	69587.926
-2 Log L	86920.451	69499.833

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The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	17420.6179	6	<.0001
Score	20932.9629	6	<.0001
Wald	12811.6281	6	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	-7.4366	0.2193	1149.5565	<.0001
lognx_5x	1	1.0403	0.0271	1471.3268	<.0001
arg_tRSDHC	1	-0.2526	0.0372	46.0545	<.0001
arg_tRSDCO	1	0.1441	0.0243	35.0917	<.0001
arg_tRSDNX	1	0.8441	0.0288	856.5727	<.0001
arg_tRSDH*arg_tRSDCO	1	0.1017	0.00851	142.9074	<.0001
arg_tRSDH*arg_tRSDNX	1	0.0389	0.00925	17.6411	<.0001

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
lognx_5x	2.830	2.684	2.985

Association of Predicted Probabilities and Observed Responses

Percent Concordant	83.7	Somers' D	0.686
Percent Discordant	15.1	Gamma	0.695
Percent Tied	1.2	Tau-a	0.045
Pairs	2811600997	c	0.843

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The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

Group	Total	tr_nx5res_pass = 1 Observed	tr_nx5res_pass = 1 Expected	tr_nx5res_pass = 0 Observed	tr_nx5res_pass = 0 Expected
1	29221	23935	24235.32	5286	4985.68
2	29200	27332	27171.08	1868	2028.92
3	29289	28289	28140.80	1000	1148.20
4	29306	28706	28613.54	600	692.46
5	29193	28806	28765.01	387	427.99
6	28934	28675	28662.44	259	271.56
7	29428	29207	29245.36	221	182.64
8	30176	30010	30050.80	166	125.20
9	29737	29634	29657.23	103	79.77
10	27574	27497	27535.03	77	38.97

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
138.0752	8	<.0001

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Table E-9. SAS Output for Equations E-22 and E-31

The LOGISTIC Procedure

Model Information

Data Set	WORK.NX5COND
Response Variable	tr_nx5res_pass
Number of Response Levels	2
Number of Observations	285266
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	tr_nx5res_ pass	Total Frequency
1	1	281005
2	0	4261

NOTE: 149859 observations were deleted due to missing values for the response or explanatory variables.

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	44285.825	38416.008
SC	44296.387	38489.937
-2 Log L	44283.825	38402.008

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	5881.8169	6	<.0001
Score	6143.0393	6	<.0001
Wald	4824.2009	6	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	-8.1634	0.3255	629.0608	<.0001
lognx_5x	1	1.4382	0.0404	1269.3713	<.0001
arg_tRSDHC	1	-0.4939	0.0540	83.6316	<.0001
arg_tRSDCO	1	0.1100	0.0371	8.7863	0.0030
arg_tRSDNX	1	0.5167	0.0425	147.9058	<.0001
arg_tRSDH*arg_tRSDCO	1	0.1045	0.0123	72.5003	<.0001
arg_tRSDH*arg_tRSDNX	1	0.0935	0.0131	50.8092	<.0001

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
lognx_5x	4.213	3.893	4.560

Association of Predicted Probabilities and Observed Responses

Percent Concordant	79.6	Somers' D	0.620
Percent Discordant	17.6	Gamma	0.638
Percent Tied	2.8	Tau-a	0.018
Pairs	1197362305	c	0.810

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

		tr_nx5res_pass = 1		tr_nx5res_pass = 0	
Group	Total	Observed	Expected	Observed	Expected
1	28533	26544	26634.39	1989	1898.61
2	28647	27817	27805.14	830	841.86
3	28574	28087	28050.74	487	523.26
4	28363	28056	28019.08	307	343.92
5	28422	28219	28187.50	203	234.50
6	29288	29145	29121.59	143	166.41
7	28265	28149	28152.93	116	112.07
8	29647	29551	29566.05	96	80.95
9	29123	29068	29072.20	55	50.80
10	26404	26369	26381.20	35	22.80

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
28.7621	8	0.0003

Table E-10. SAS Output for Equations E-2 and E-5

The LOGISTIC Procedure

Model Information

Data Set	WORK.HCUNC
Response Variable	tr_hcres_pass
Number of Response Levels	2
Number of Observations	292058
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	tr_hcres_pass	Total Frequency
1	1	283148
2	0	8910

NOTE: 143067 observations were deleted due to missing values for the response or explanatory variables.

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	79735.217	63428.778
SC	79745.801	63502.871
-2 Log L	79733.217	63414.778

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	16318.4389	6	<.0001
Score	26425.9518	6	<.0001
Wald	13398.0068	6	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	-0.2065	0.0815	6.4249	0.0113
l_FprobHC	1	-0.5993	0.0858	48.7812	<.0001
l_FprobCO	1	-0.0841	0.0598	1.9772	0.1597
l_FprobNX	1	-0.2629	0.0483	29.5772	<.0001
l_FprobHC*l_FprobCO	1	0.0588	0.0146	16.2070	<.0001
l_FprobHC*l_FprobNX	1	-0.1523	0.0199	58.3271	<.0001
l_FprobCO*l_FprobNX	1	0.0861	0.0236	13.2955	0.0003

Association of Predicted Probabilities and Observed Responses

Percent Concordant	83.8	Somers' D	0.691
Percent Discordant	14.7	Gamma	0.702
Percent Tied	1.5	Tau-a	0.041
Pairs	2522848680	c	0.846

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

		tr_hcres_pass = 1		tr_hcres_pass = 0	
Group	Total	Observed	Expected	Observed	Expected
1	29213	24313	24381.66	4900	4831.34
2	29255	27683	27677.49	1572	1577.51
3	29296	28474	28444.26	822	851.74
4	29253	28724	28707.65	529	545.35
5	29376	29014	29001.18	362	374.82
6	28791	28564	28531.31	227	259.69
7	29390	29213	29198.80	177	191.20
8	28976	28830	28838.97	146	137.03
9	29385	29284	29286.37	101	98.63
10	29123	29049	29065.87	74	57.13

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
14.0519	8	0.0804

Table E-11. SAS Output for Equations E-3 and E-6

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The LOGISTIC Procedure

Model Information

Data Set	WORK.COCON
Response Variable	tr_cores_pass
Number of Response Levels	2
Number of Observations	283148
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	tr_cores_ pass	Total Frequency
1	1	282254
2	0	894

NOTE: 151977 observations were deleted due to missing values for the response or explanatory variables.

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	12082.513	10342.695
SC	12093.066	10406.017
-2 Log L	12080.513	10330.695

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The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	1749.8178	5	<.0001
Score	2797.2980	5	<.0001
Wald	1523.0843	5	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	2.0643	0.2199	88.1313	<.0001
l_FprobHC	1	2.4753	0.1917	166.6664	<.0001
l_FprobCO	1	-1.7651	0.1087	263.6407	<.0001
l_FprobNX	1	-0.8651	0.1305	43.9707	<.0001
l_FprobHC*l_FprobCO	1	0.3876	0.0389	99.2522	<.0001
l_FprobCO*l_FprobNX	1	-0.2893	0.0366	62.5840	<.0001

Association of Predicted Probabilities and Observed Responses

Percent Concordant	76.9	Somers' D	0.665
Percent Discordant	10.4	Gamma	0.761
Percent Tied	12.6	Tau-a	0.004
Pairs	252335076	c	0.832

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The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

Group	Total	tr_cores_pass = 1 Observed	tr_cores_pass = 1 Expected	tr_cores_pass = 0 Observed	tr_cores_pass = 0 Expected
1	28286	27750	27781.15	536	504.85
2	28258	28122	28106.44	136	151.56
3	29208	29134	29119.73	74	88.27
4	29227	29181	29170.62	46	56.38
5	29518	29492	29479.79	26	38.21
6	26680	26664	26655.84	16	24.16
7	24972	24955	24955.54	17	16.46
8	35554	35533	35537.71	21	16.29
9	21012	21001	21005.43	11	6.57
10	30433	30422	30427.65	11	5.35

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
24.7904	8	0.0017

Table E-12. SAS Output for Equations E-4 and E-7

The LOGISTIC Procedure

Model Information

Data Set	WORK.NXCON
Response Variable	tr_nxres_pass
Number of Response Levels	2
Number of Observations	282254
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	tr_nxres_ pass	Total Frequency
1	1	274463
2	0	7791

NOTE: 152871 observations were deleted due to missing values for the response or explanatory variables.

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	71303.798	59356.312
SC	71314.349	59409.064
-2 Log L	71301.798	59346.312

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	11955.4866	4	<.0001
Score	13993.1754	4	<.0001
Wald	8777.9849	4	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	0.7462	0.0924	65.2130	<.0001
l_FprobHC	1	0.7101	0.0406	305.7352	<.0001
l_FprobCO	1	-0.2863	0.0358	64.0988	<.0001
l_FprobNX	1	-0.9648	0.0198	2371.7147	<.0001
l_FprobHC*l_FprobCO	1	0.0479	0.00784	37.3635	<.0001

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
l_FprobNX	0.381	0.367	0.396

Association of Predicted Probabilities and Observed Responses

Percent Concordant	82.1	Somers' D	0.657
Percent Discordant	16.4	Gamma	0.666
Percent Tied	1.5	Tau-a	0.035
Pairs	2138341233	c	0.828

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

		tr_nxres_pass = 1		tr_nxres_pass = 0	
Group	Total	Observed	Expected	Observed	Expected
1	28229	24462	24639.50	3767	3589.50
2	28291	26648	26663.63	1643	1627.37
3	28306	27420	27333.33	886	972.67
4	28348	27858	27738.30	490	609.70
5	28429	28124	28040.32	305	388.68
6	28477	28241	28226.07	236	250.93
7	28216	28049	28053.08	167	162.92
8	29036	28902	28926.72	134	109.28
9	28812	28711	28746.14	101	65.86
10	26110	26048	26081.91	62	28.09

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
126.8993	8	<.0001

Figure E-1. Linearization Check for Equations E-14 and E-23 (Training Data)

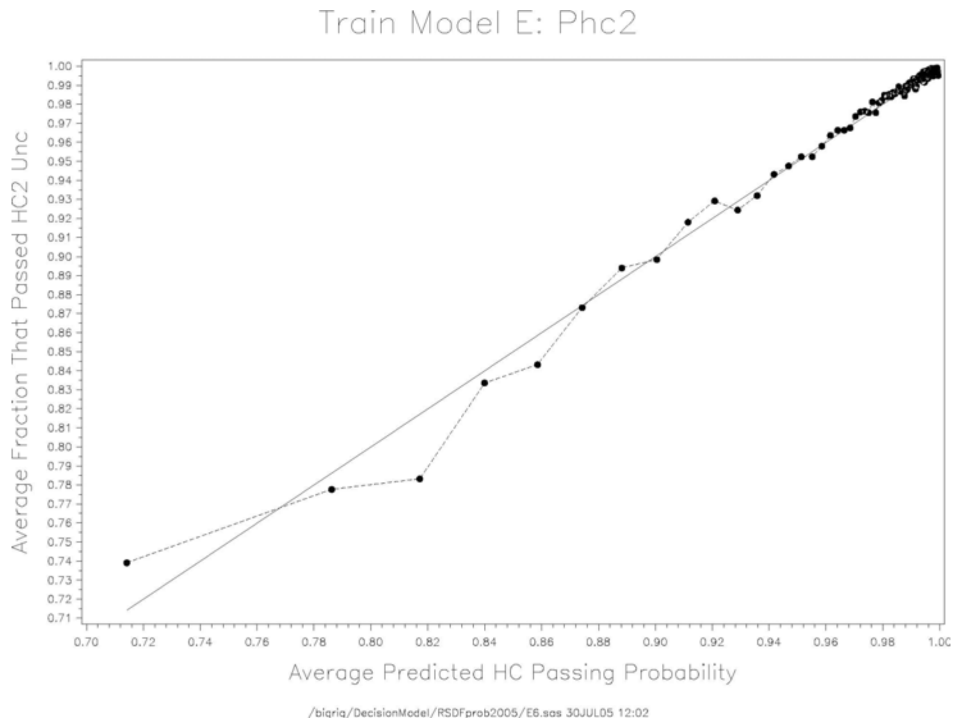


Figure E-2. Linearization Check for Equations E-15 and E-24 (Training Data)

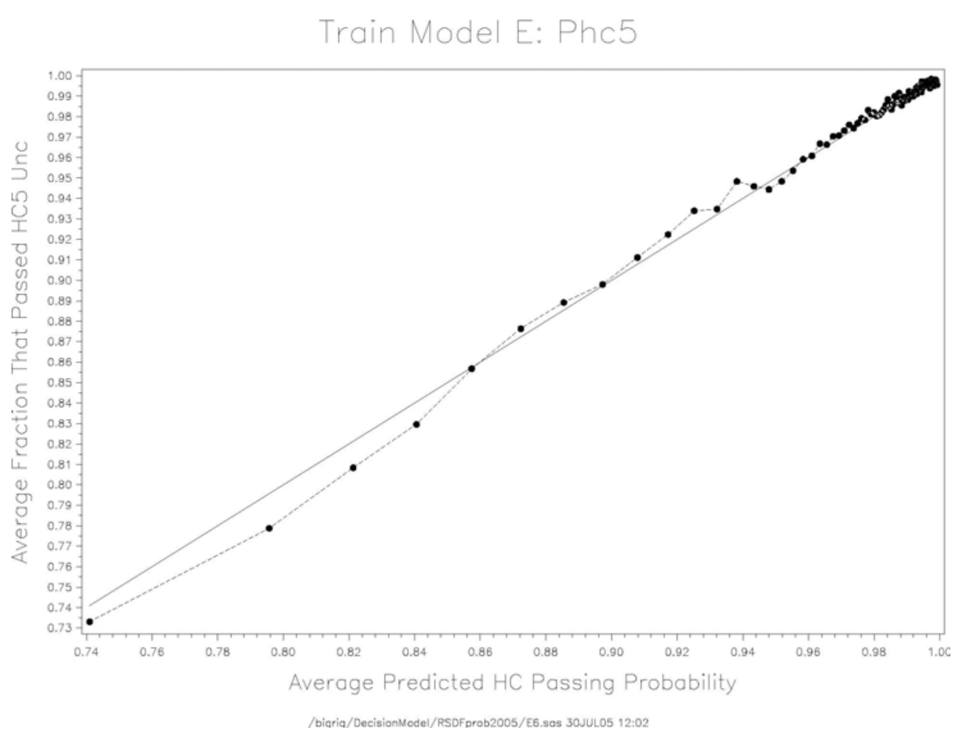


Figure E-3. Linearization Check for Equations E-16 and E-25 (Training Data)

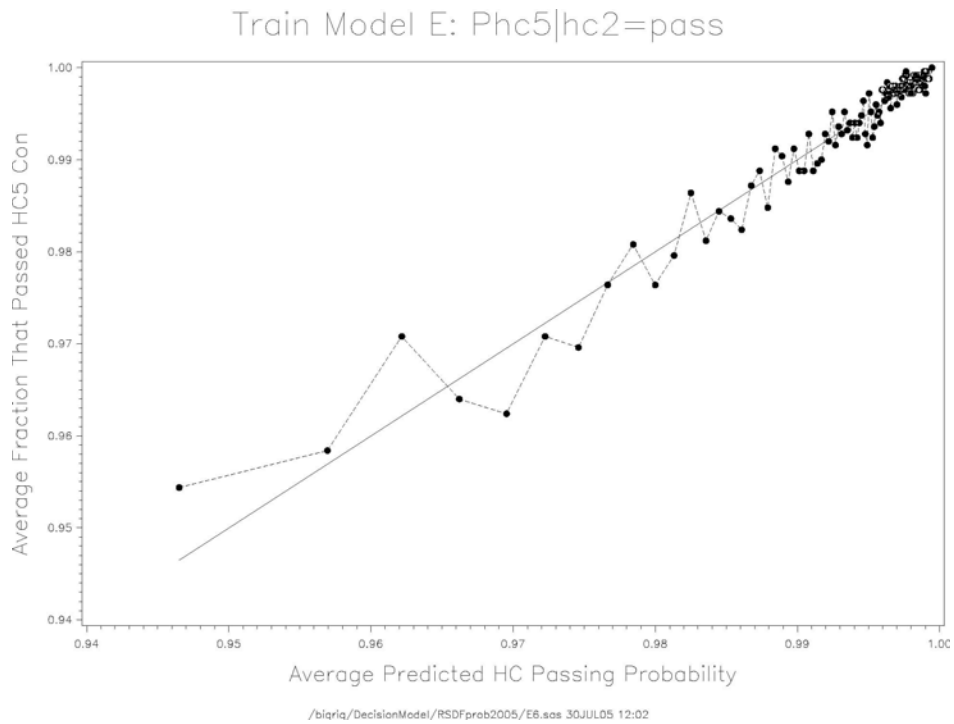


Figure E-4. Linearization Check for Equations E-17 and E-26 (Training Data)

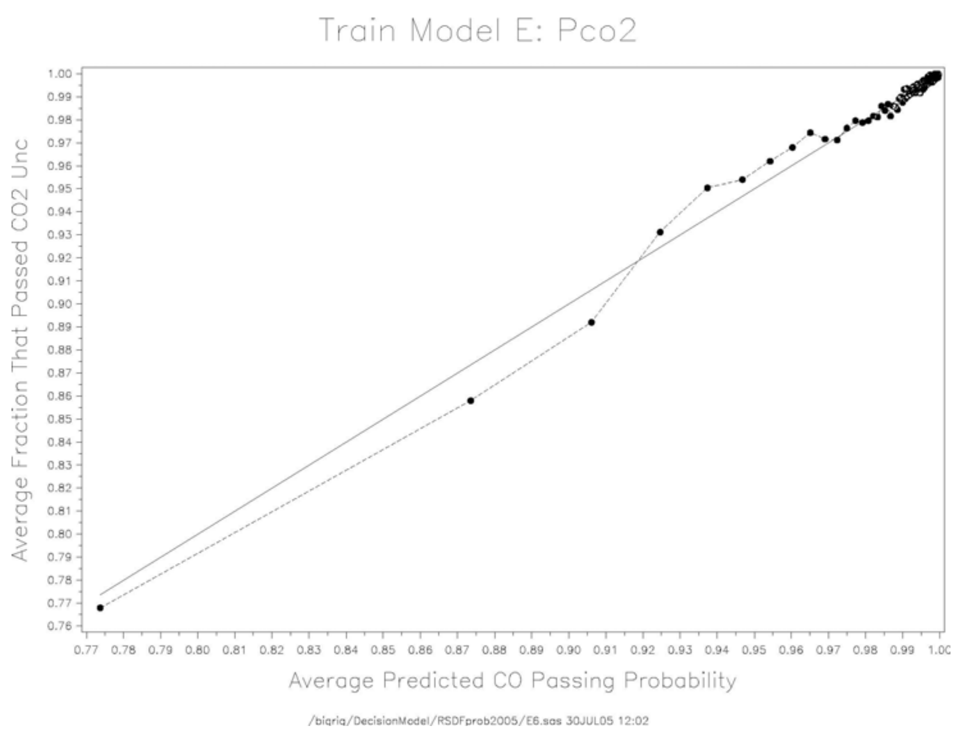


Figure E-5. Linearization Check for Equations E-18 and E-27 (Training Data)

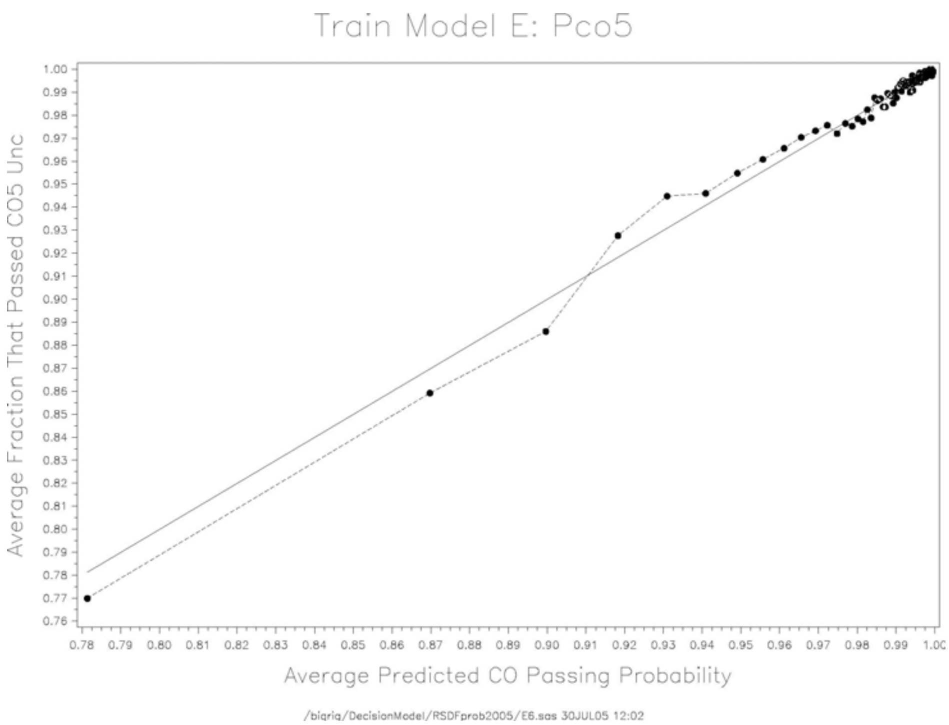


Figure E-6. Linearization Check for Equations E-19 and E-28 (Training Data)

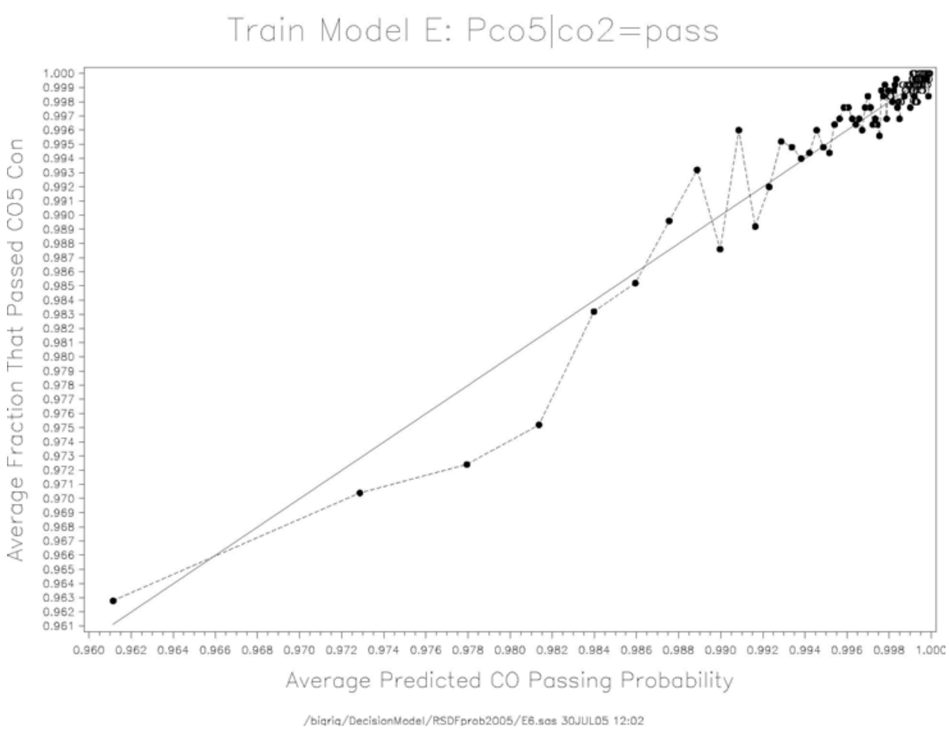


Figure E-7. Linearization Check for Equations E-20 and E-29 (Training Data)

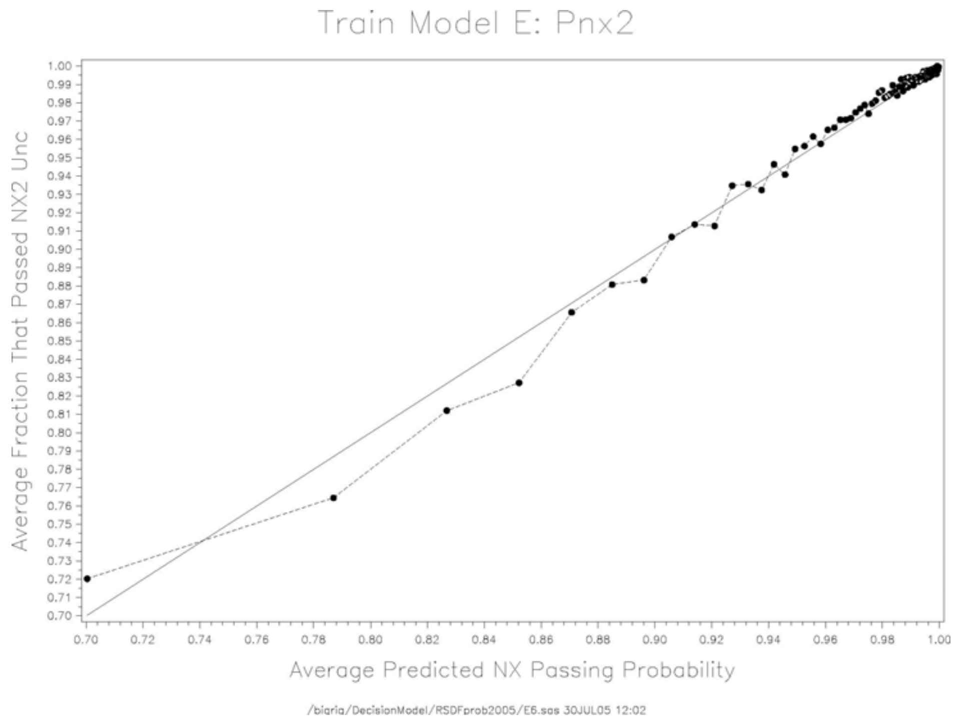


Figure E-8. Linearization Check for Equations E-21 and E-30 (Training Data)

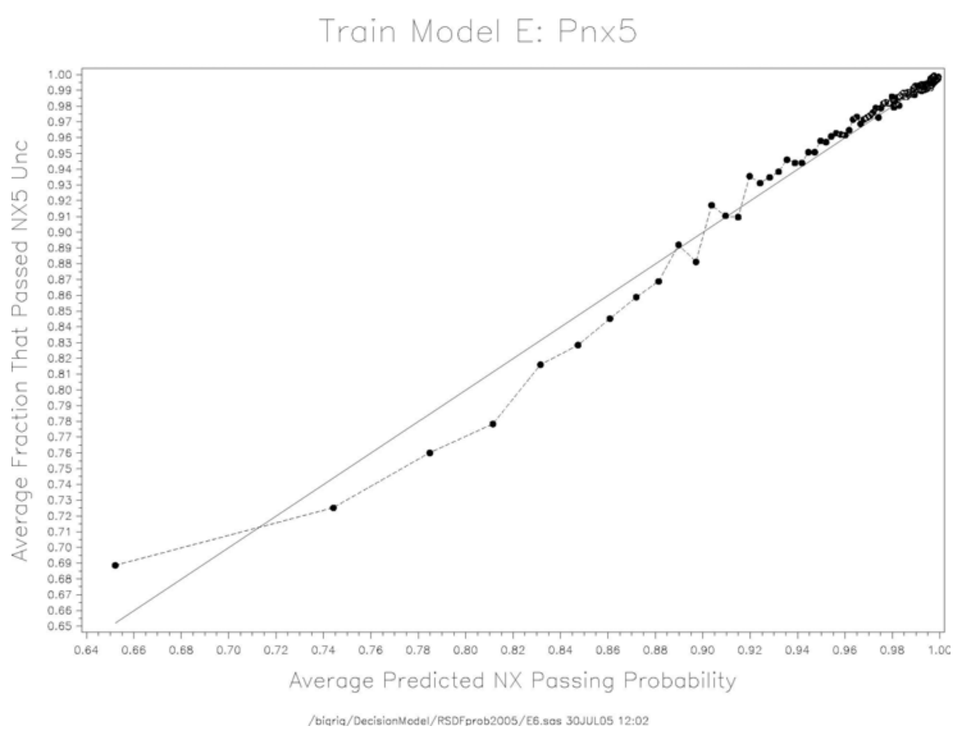


Figure E-9. Linearization Check for Equations E-22 and E-31 (Training Data)

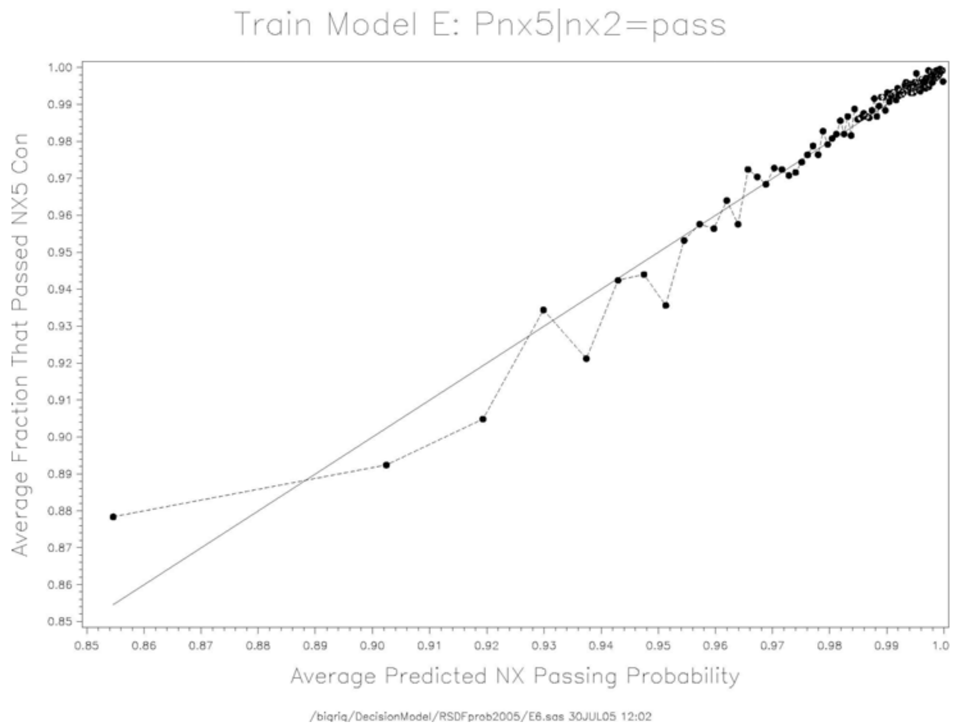


Figure E-10. Linearization Check for Equations E-11 (Training Data)

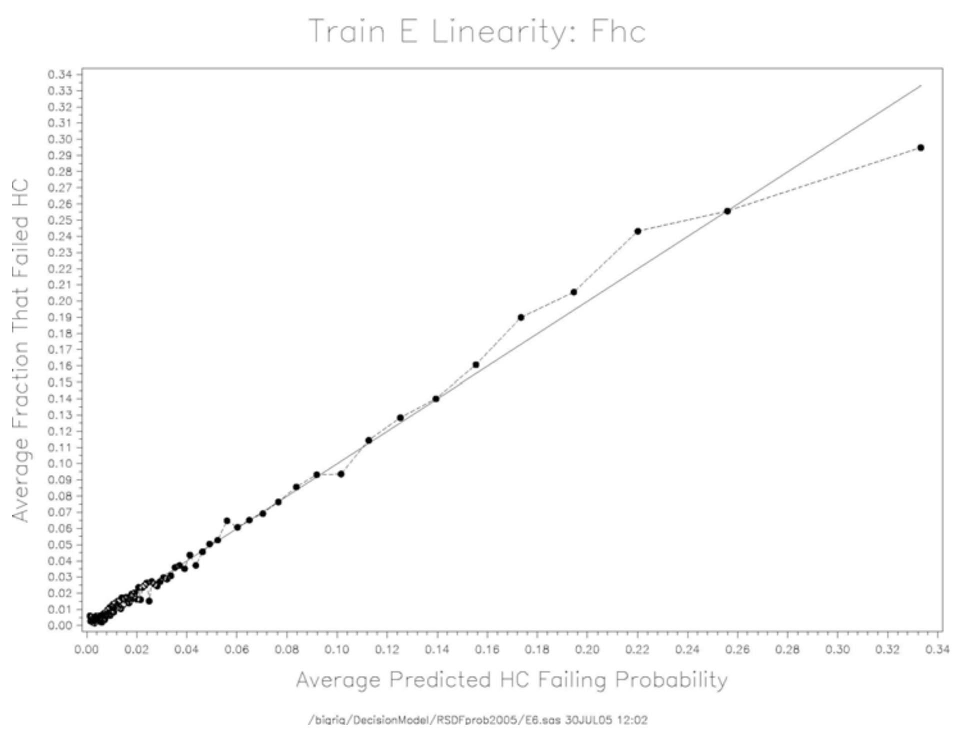


Figure E-11. Linearization Check for Equations E-12 (Training Data)

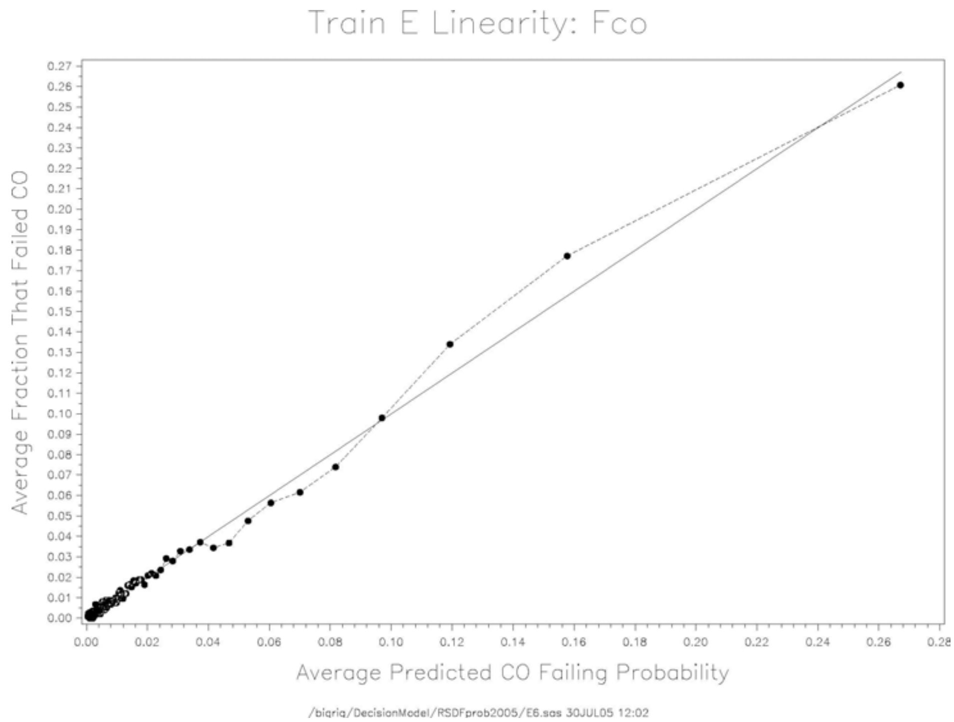


Figure E-12. Linearization Check for Equations E-13 (Training Data)

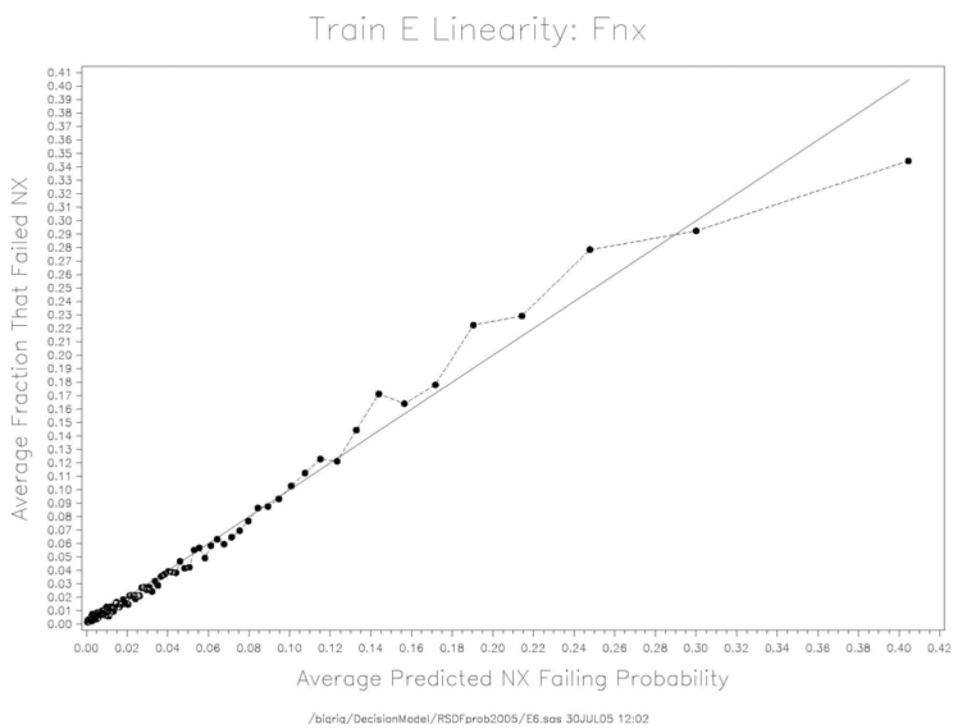


Figure E-13. Linearization Check for Equations E-14 and E-23 (Validation Data)

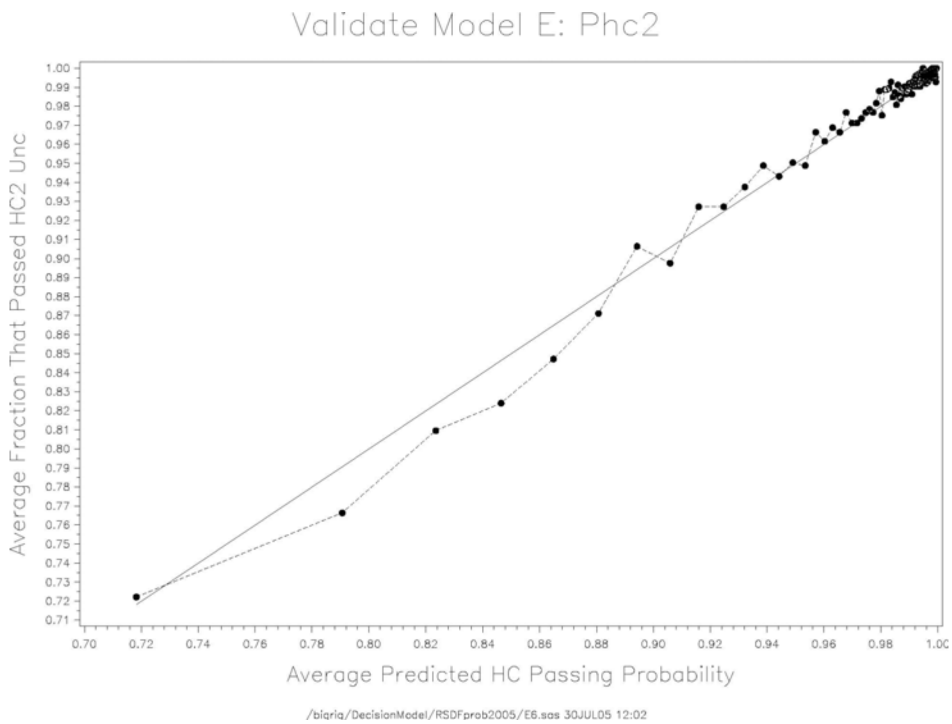


Figure E-14. Linearization Check for Equations E-15 and E-24 (Validation Data)

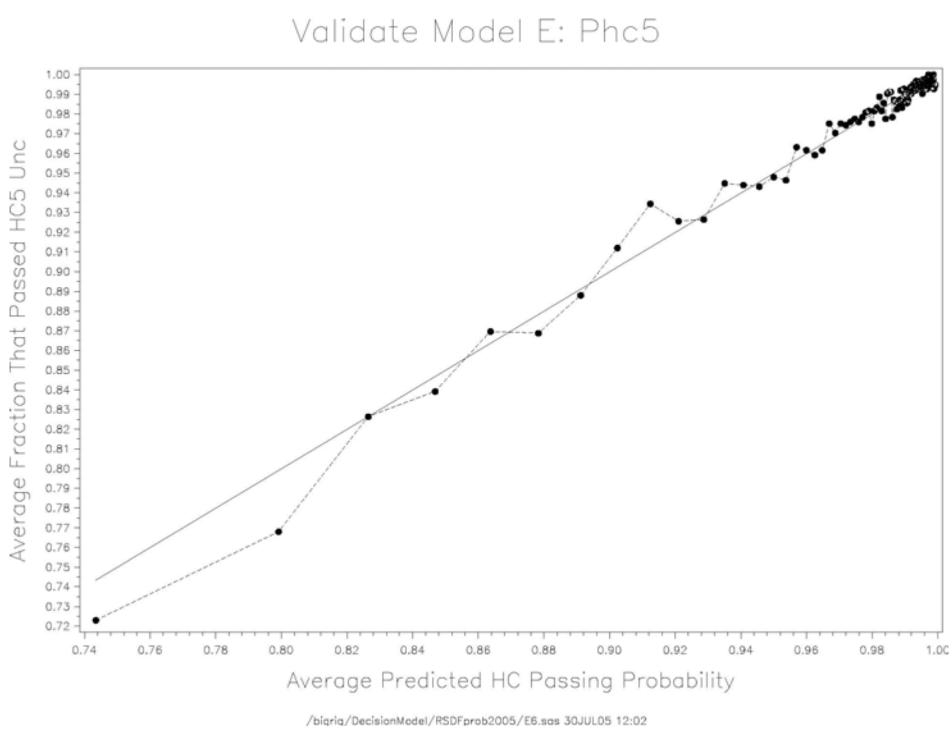


Figure E-15. Linearization Check for Equations E-16 and E-25 (Validation Data)

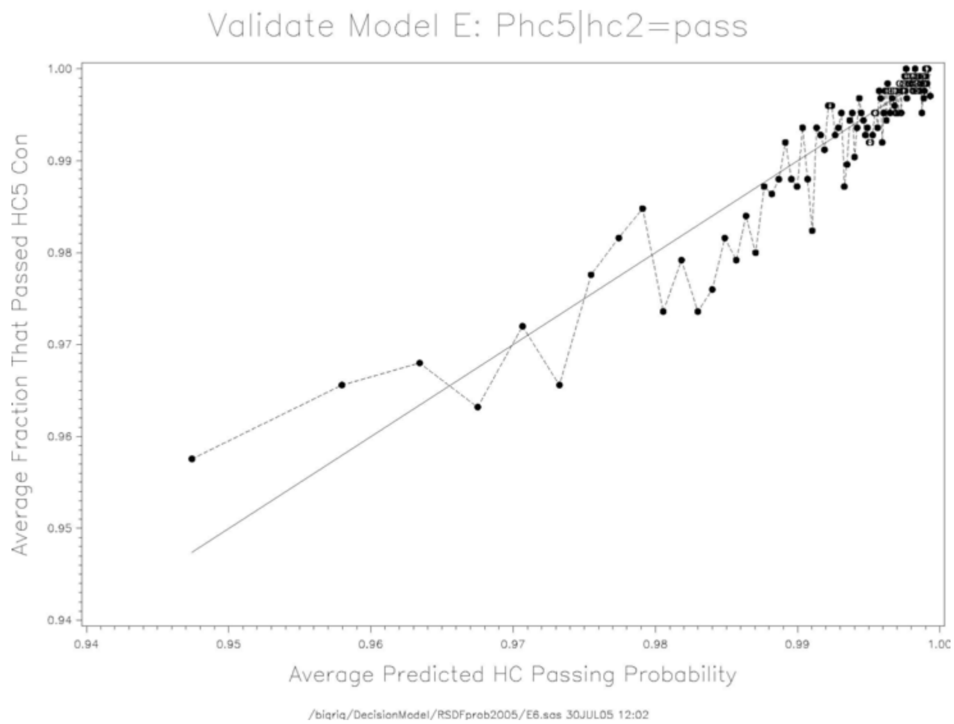


Figure E-16. Linearization Check for Equations E-17 and E-26 (Validation Data)

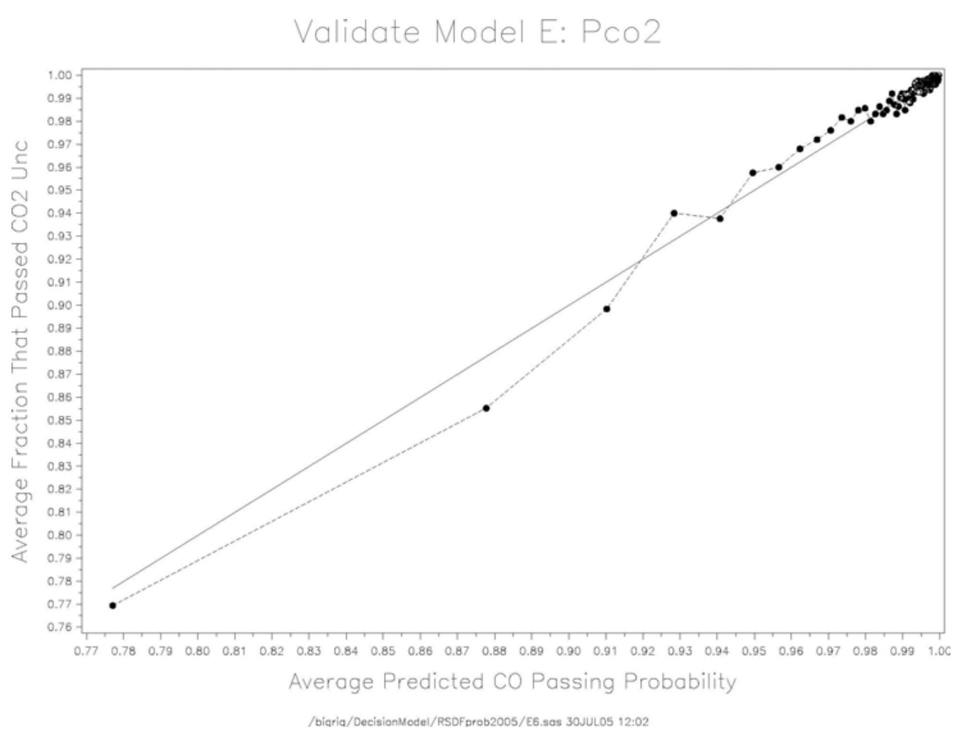


Figure E-17. Linearization Check for Equations E-18 and E-27 (Validation Data)

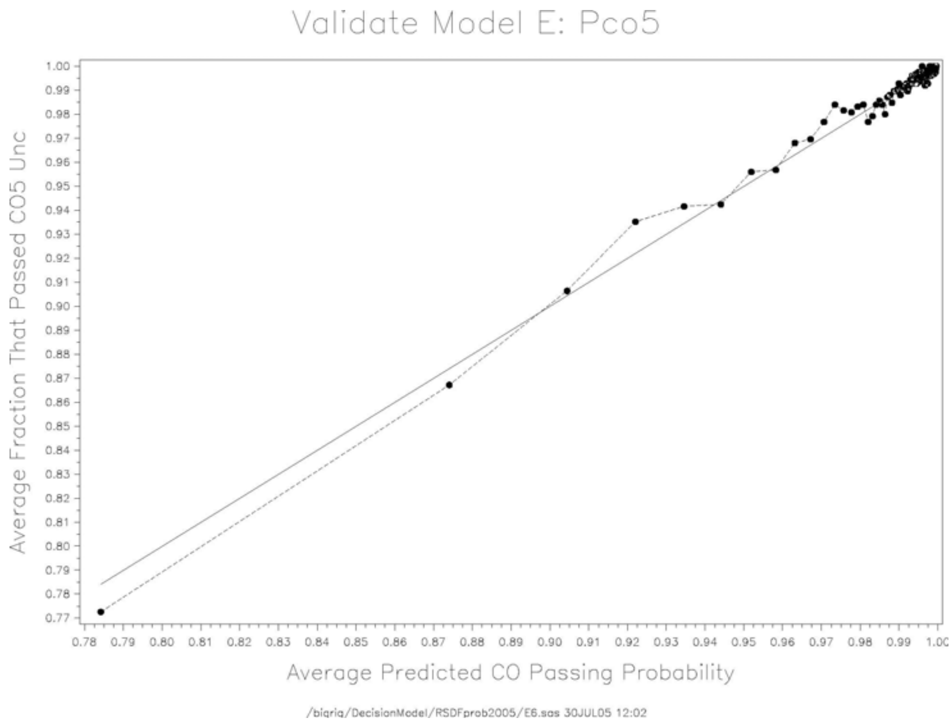


Figure E-18. Linearization Check for Equations E-19 and E-28 (Validation Data)

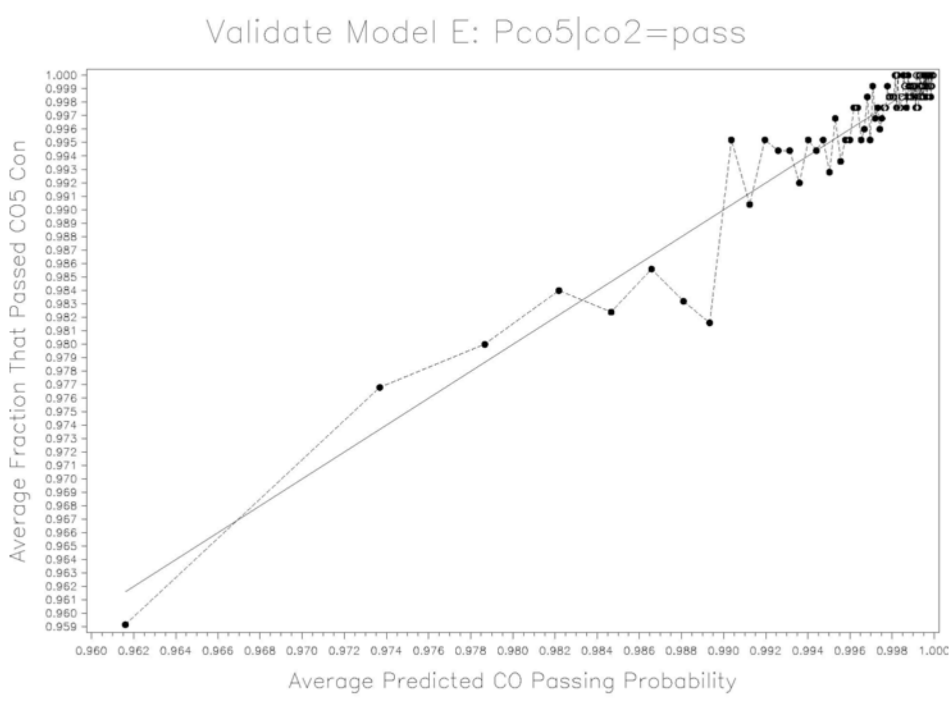


Figure E-19. Linearization Check for Equations E-20 and E-29 (Validation Data)

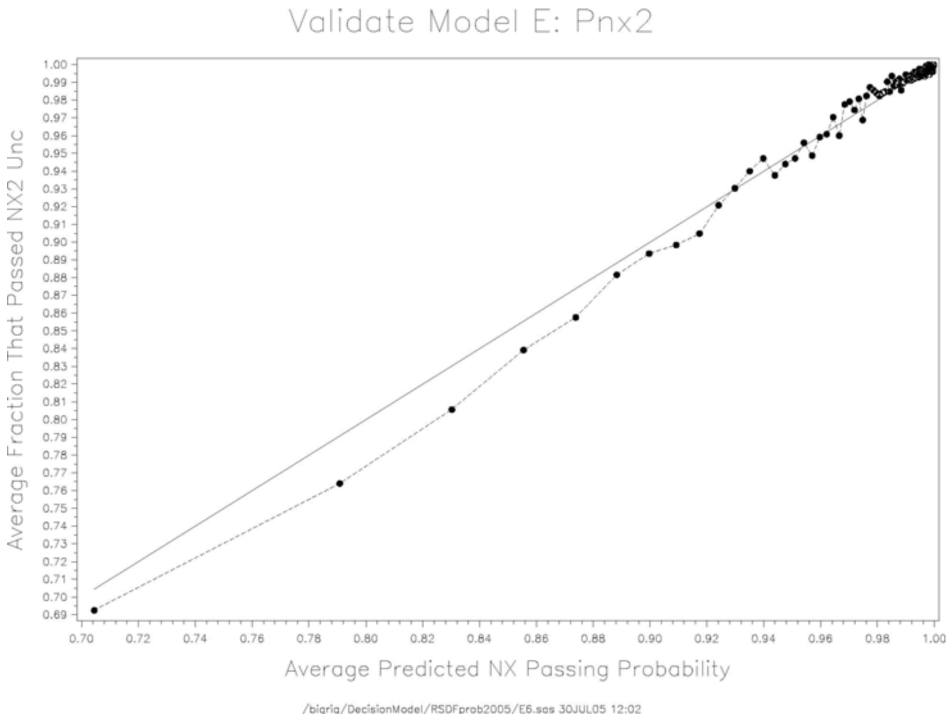


Figure E-20. Linearization Check for Equations E-21 and E-30 (Validation Data)

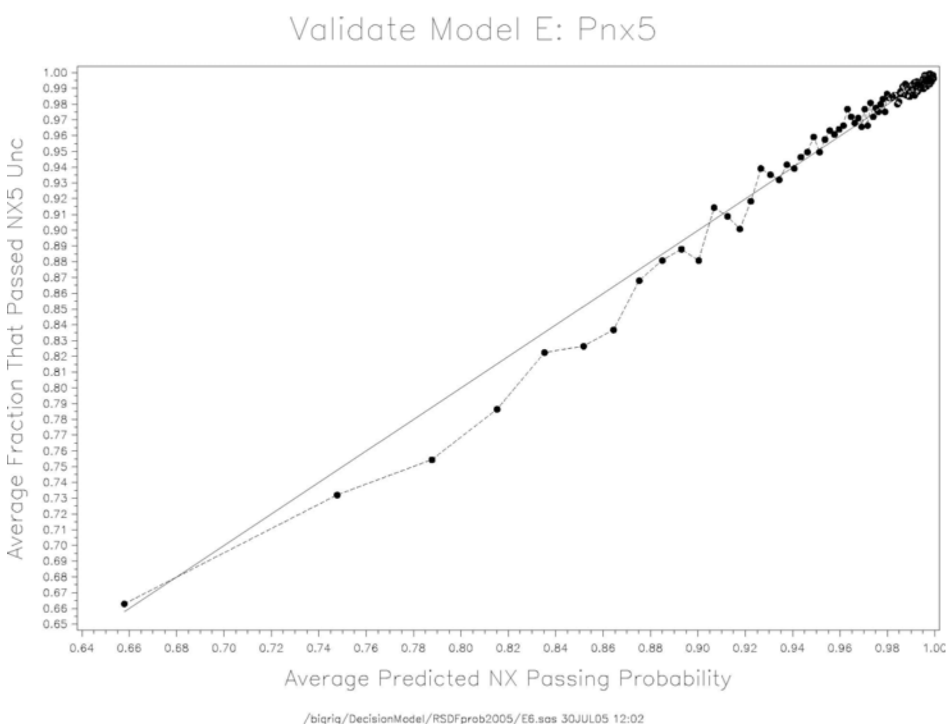


Figure E-21. Linearization Check for Equations E-22 and E-31 (Validation Data)

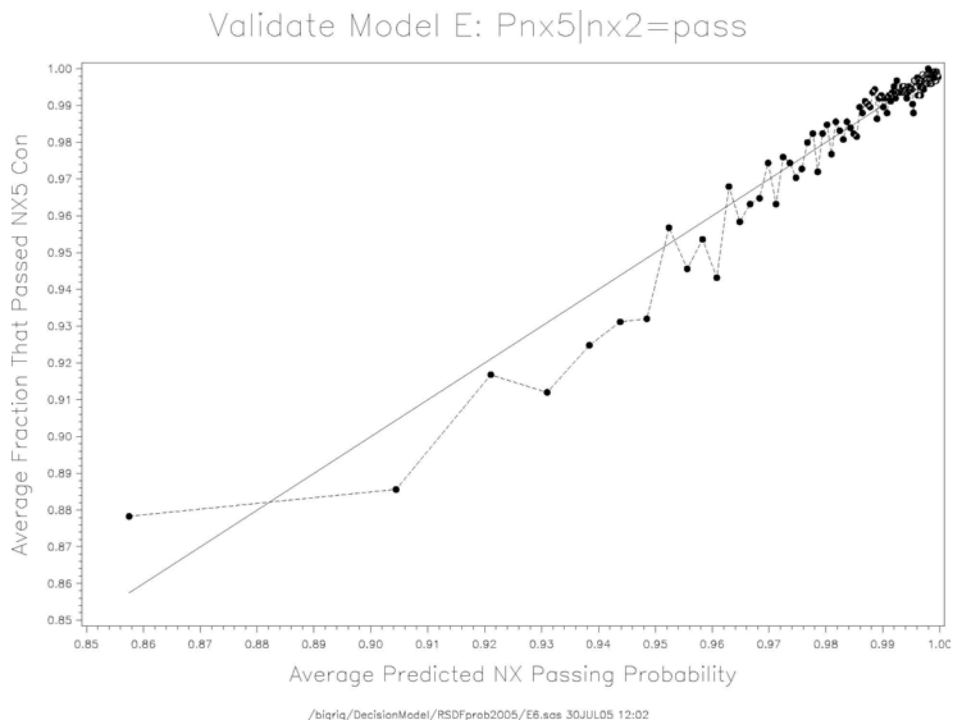


Figure E-22. Linearization Check for Equations E-11 (Validation Data)

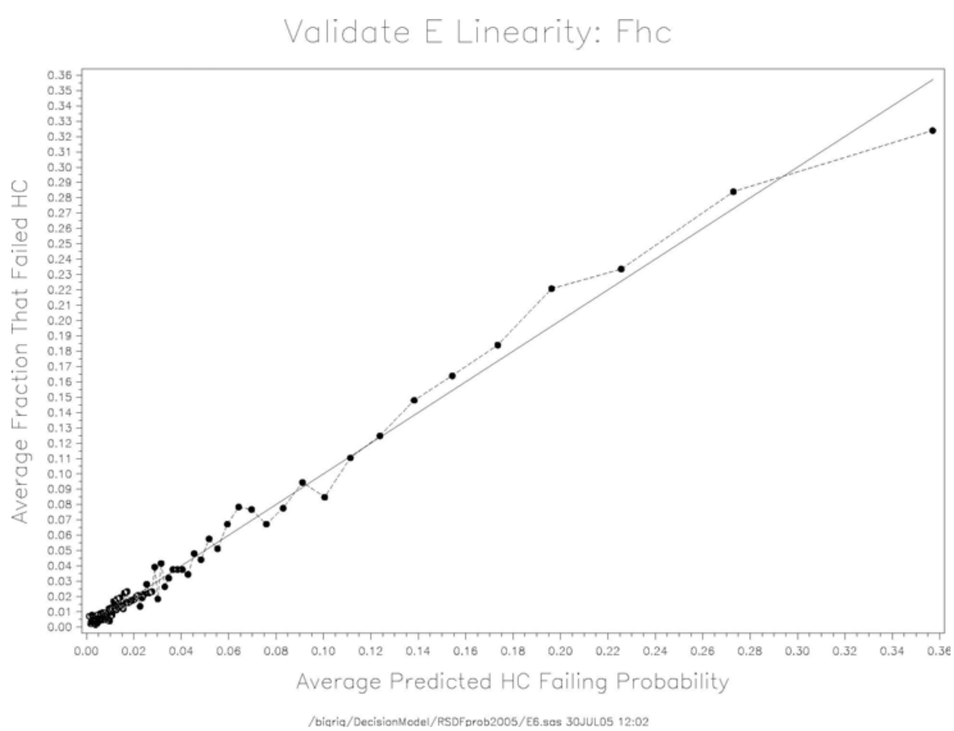


Figure E-23. Linearization Check for Equations E-12 (Validation Data)

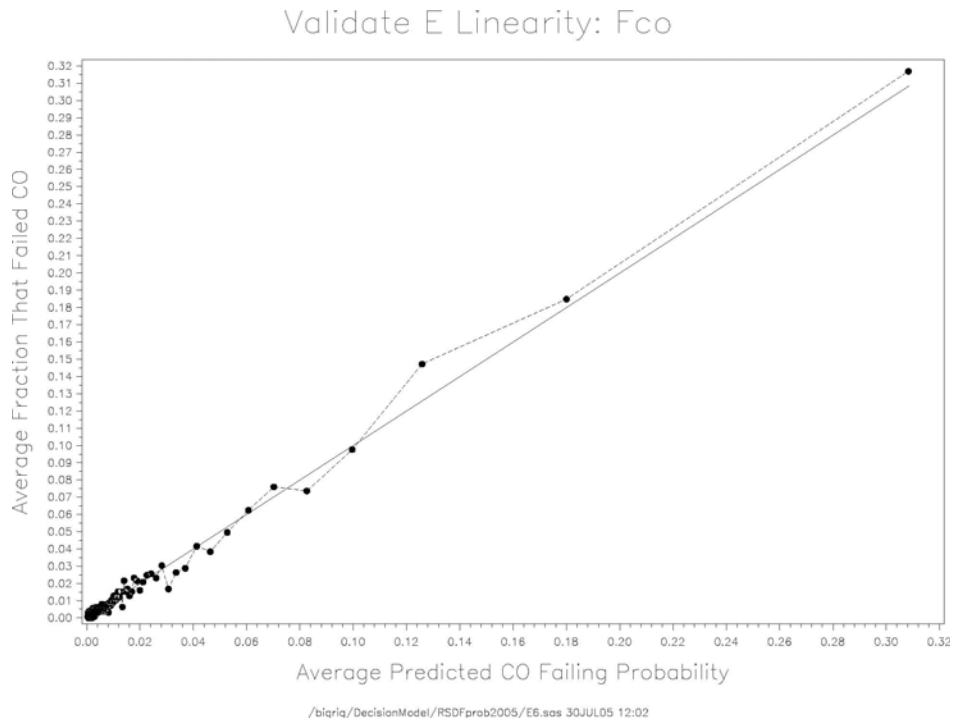


Figure E-24. Linearization Check for Equations E-13 (Validation Data)

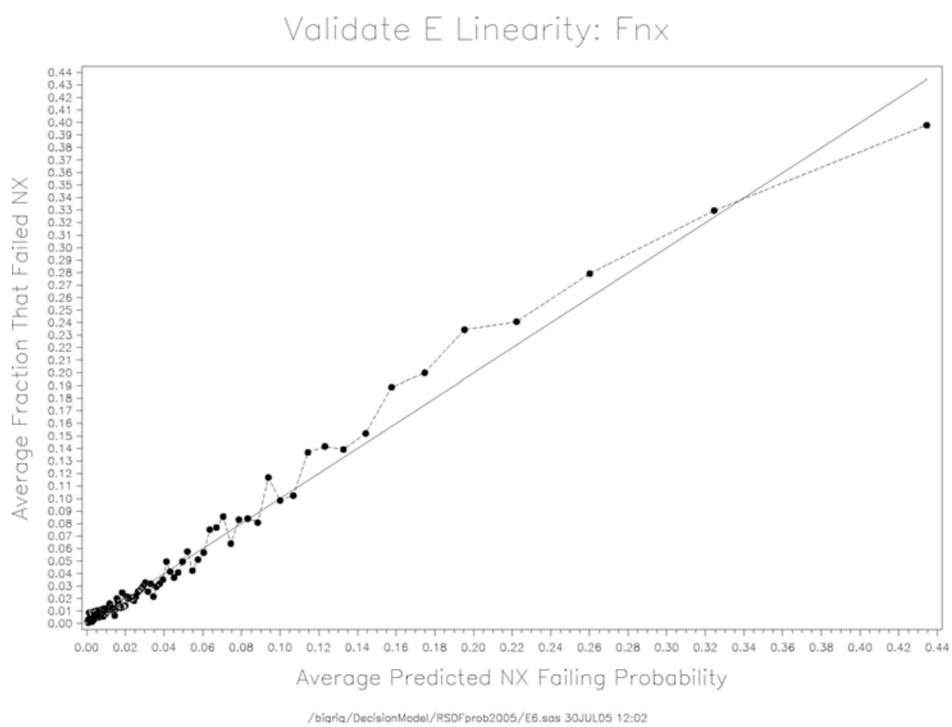


Figure E-25. Linearization Check for Equations E-2 and E-5 (Training Data)

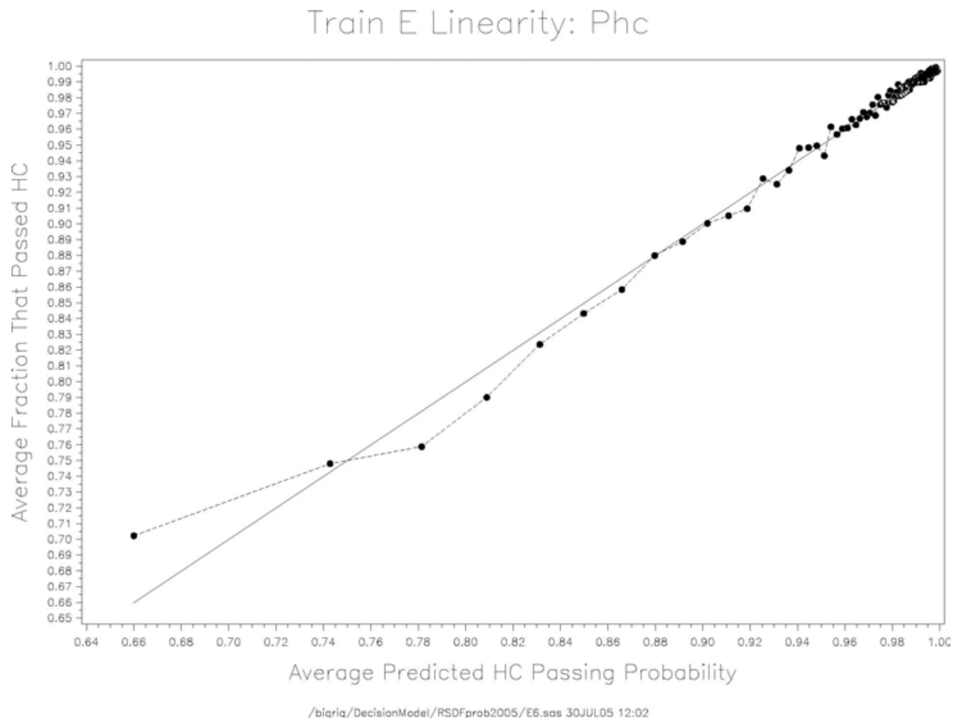


Figure E-26. Linearization Check for Equations E-3 and E-6 (Training Data)

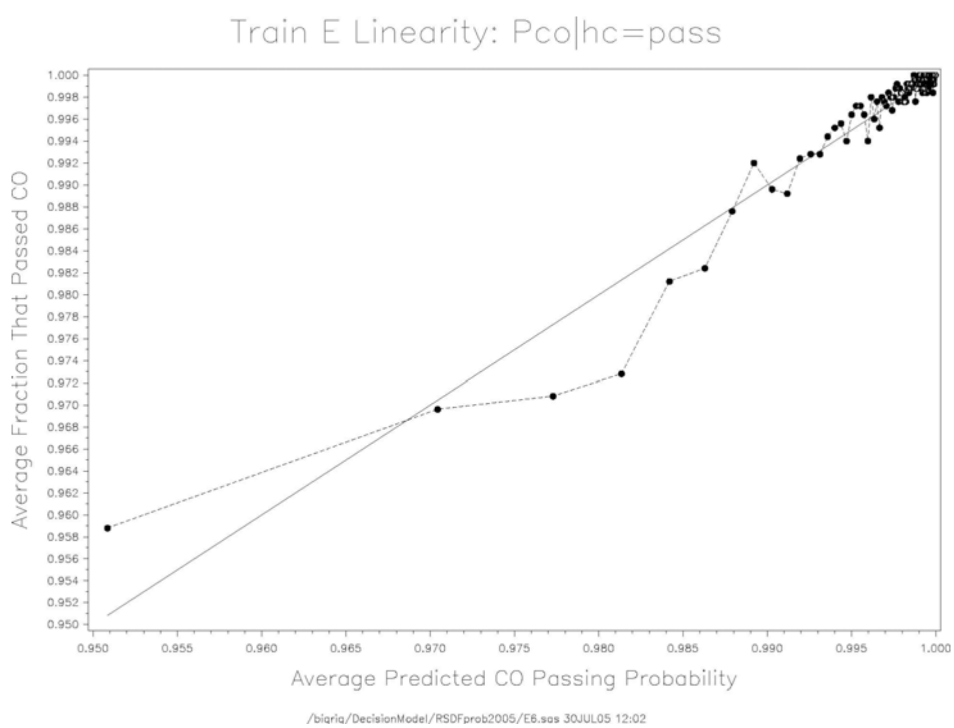


Figure E-27. Linearization Check for Equations E-4 and E-7 (Training Data)

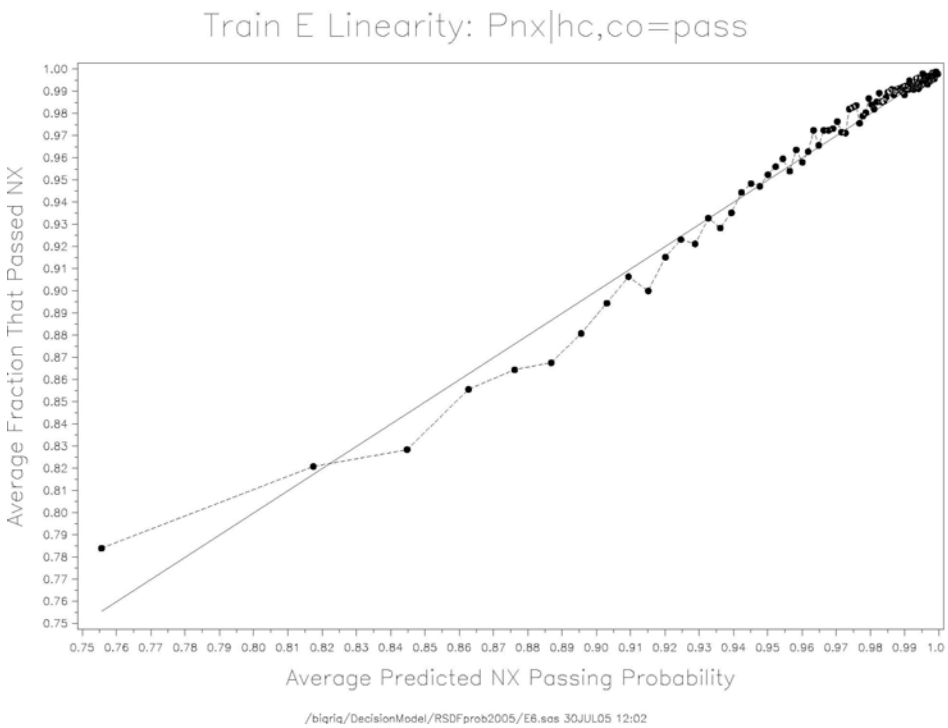


Figure E-28. Linearization Check for Equations E-1 (Training Data)

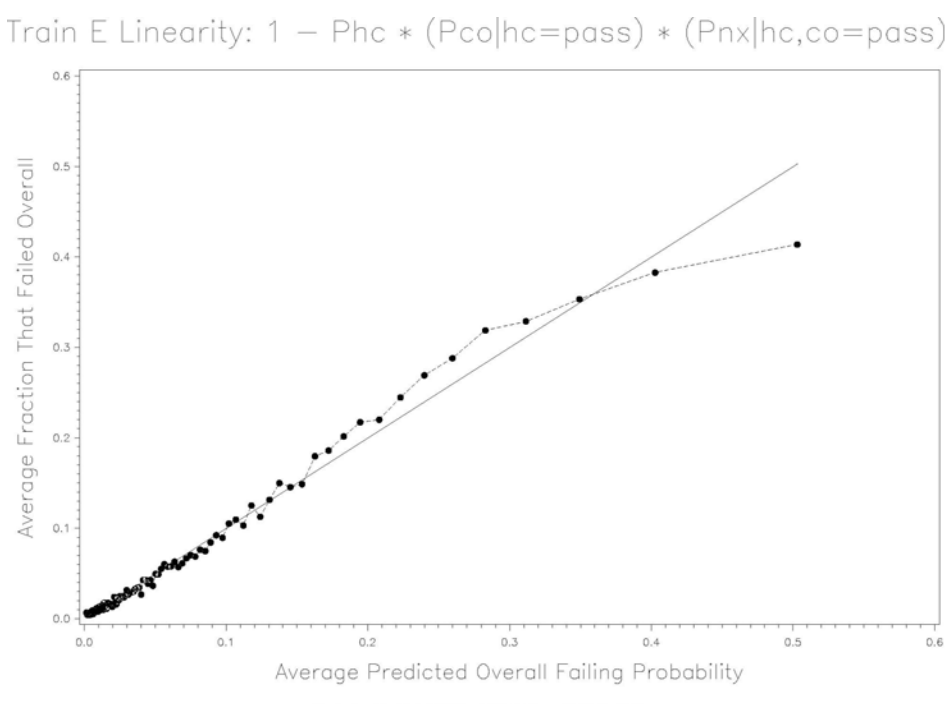


Figure E-29. Linearization Check for Equations E-2 and E-5 (Validation Data)

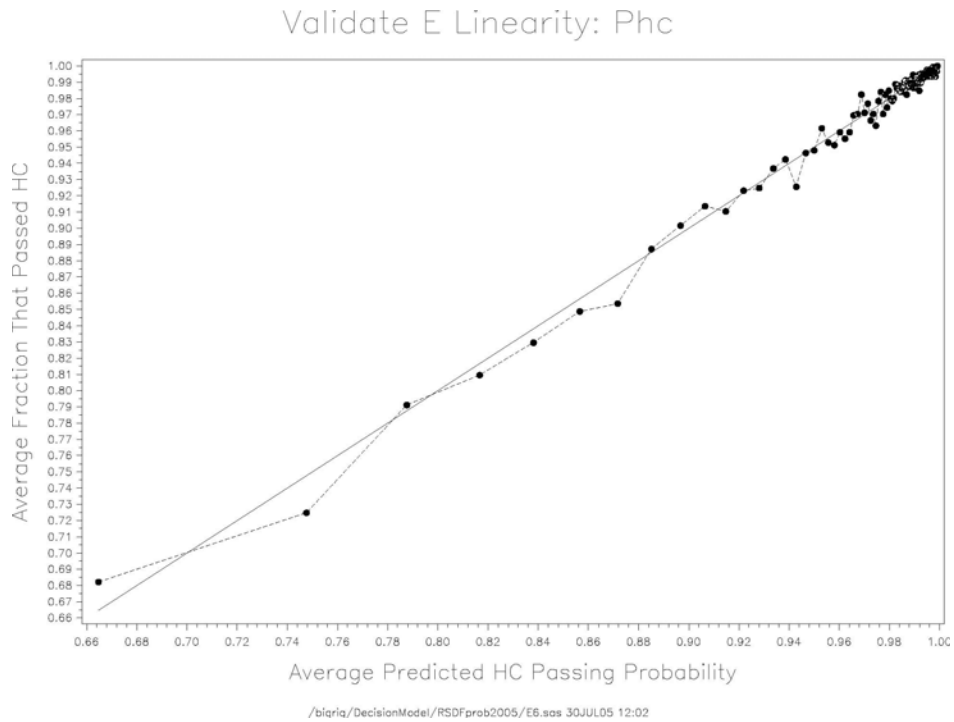


Figure E-30. Linearization Check for Equations E-3 and E-6 (Validation Data)

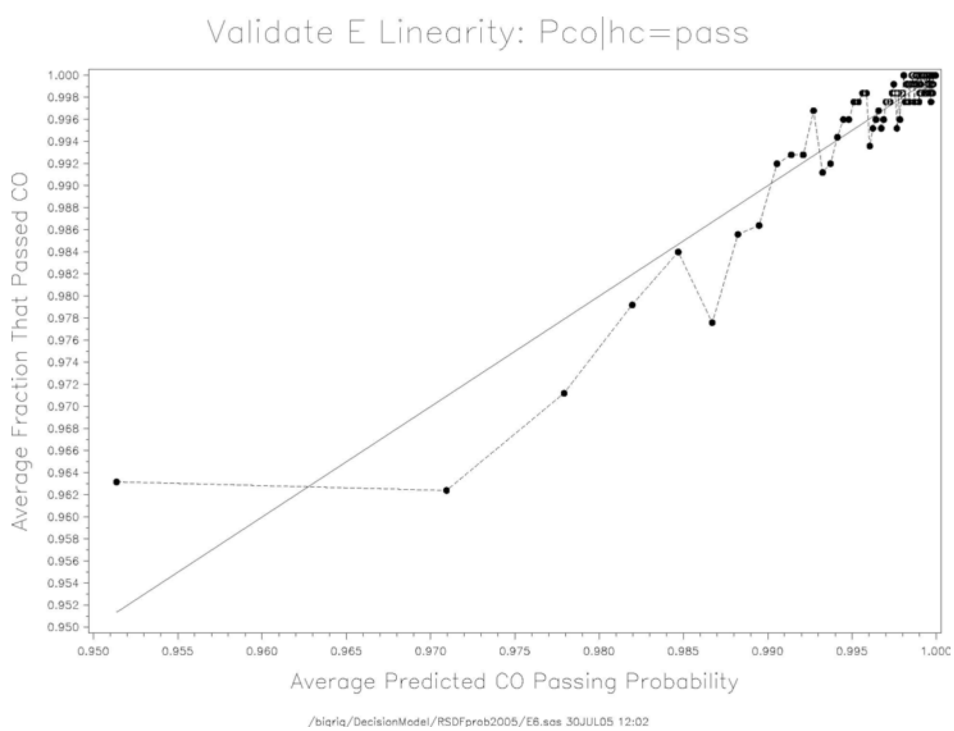


Figure E-31. Linearization Check for Equations E-4 and E-7 (Validation Data)

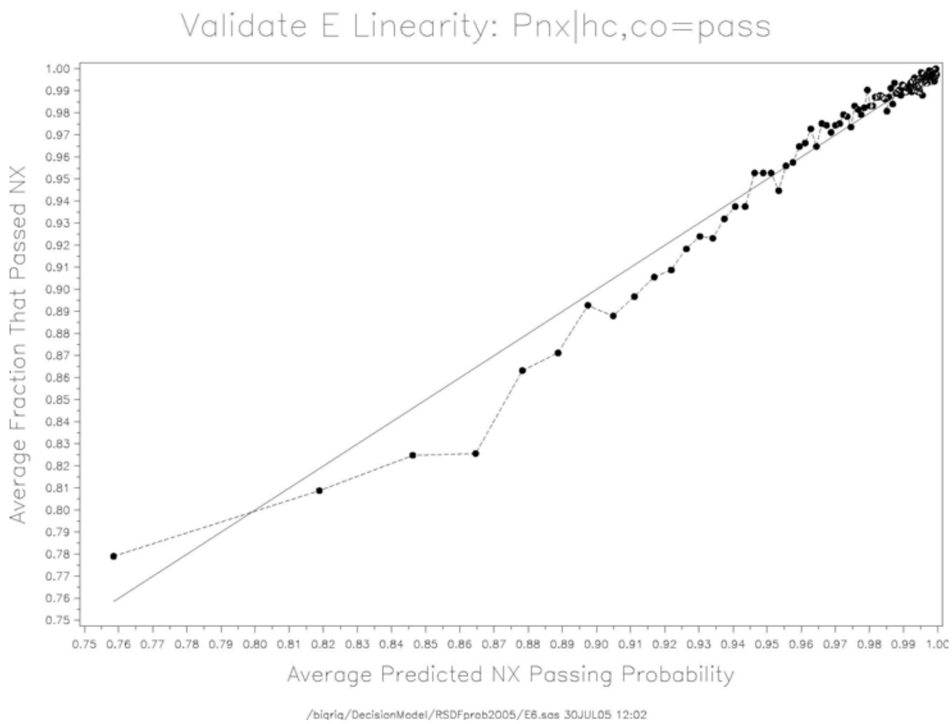
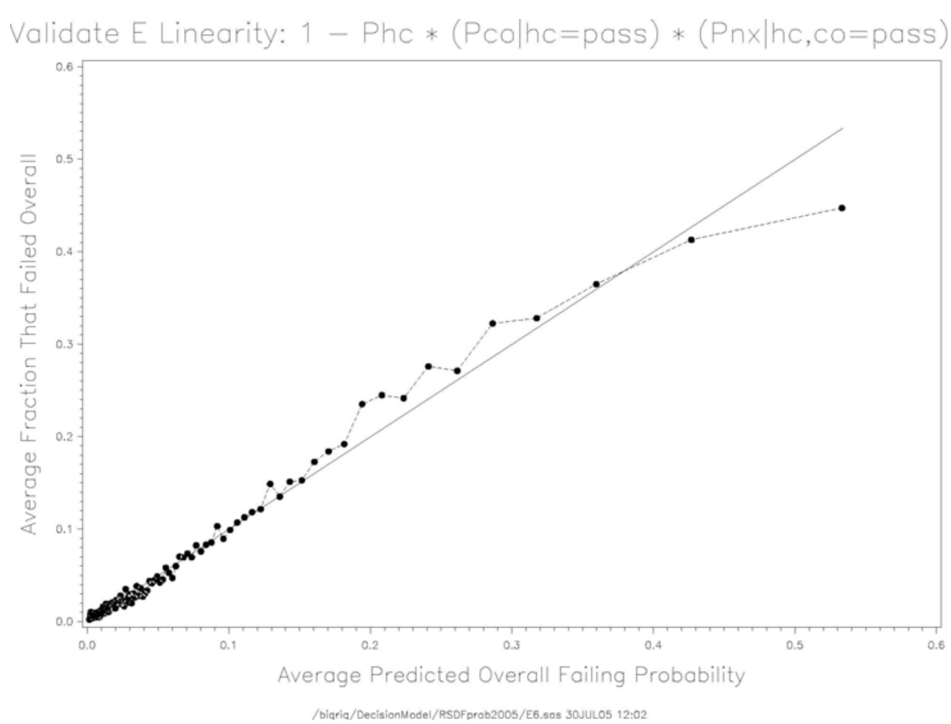


Figure E-32. Linearization Check for Equations E-1 (Validation Data)



Appendix F

Model F ASM Failure Probability Equations

One of the problems with using remote sensing measurements to predict whether a vehicle will pass or fail its overall ASM test when it comes in for its inspection, is that the three RSD measures for HC, CO, and NX and the six ASM mode/pollutants are not independent of each other. While so-called RSD cutpoints can be devised and applied separately to RSD HC, RSD CO, and RSD NX, that approach can lead to more errors in overall ASM pass/fail calls. We believe that by considering the separate relationships of the three RSD measurements to the ASM mode/pollutant results, we can build a better model to predict overall ASM failure probability.

The Model F equations do not contain any explicit vehicle aging functionality. While the RSD values of vehicles will tend to increase as the vehicles age, the equations for Model F do not allow the forecasting of failure probabilities from a single RSD measurement at one point in time. The dataset used to build the Model F equations was created using RSD measurements taken between March 2004 and February 2005 and for initial cycle ASM tests that follow the RSD measurements which were taken between March 2004 and July 2005. Accordingly, the failure probability values calculated by the Model F equations are based on the ASM cutpoint values that were in effect during this period of time. Consequently, the Model F equations will produce erroneous Fprob values if different cutpoints are used. Because Model F equations do not contain any time dependence, all forecasted Fprob values using Model F are constant. Because the Model F equations do not contain ASM cutpoint functionality, they cannot be integrated to produce expected ASM emission concentrations for individual vehicles.

The goal of the Model F equations[40] is to predict overall ASM failure probability based solely on measurements of RSD HC, RSD CO, and RSD NX. The dataset containing 87,025 observations with paired RSD values and the initial cycle ASM results that follow them was used to build and validate these equations. The models were built on a randomly selected 2/3 (58,282 observations) of the dataset. The remaining 28,743 observations were set aside for model validation. While the inputs to the equations are the RSD measurements, those measurements must be first transformed to make them relatively linear. This is done by the equations G-2, G-7, and G-10 given in Appendix G. Three models given by Equations F-2, F-3, and F-4 need to be built on appropriate datasets to discover the coefficients for the linearized RSD measurements. The predicted values for these three equations are then combined using probability theory as described in Equation F-1 to properly account for the interdependences of the ASM pollutant passing probabilities.

[40] The Model F equations were developed and validated by /bigrig/DecisionModel/RSDFprob2005/F5.sas.

The six ASM mode/pollutant pass/fail results were used to determine the three ASM pollutant results. For example, if either ASM2525 HC or ASM5015 HC is a fail, then the ASM HC is a fail. Otherwise, the ASM HC is a pass. These ASM pollutant pass/fail variables were used as the response variables in the logistic regression and the transformed RSD HC, RSD CO, and RSD NX and their two-factor interactions were used as candidate predictor variables.

Logistic regressions were performed on the three datasets that reflected the conditionality of the passing probabilities to be determined. This is shown by the number of observations in Table F-1. To model the passing probability for ASM HC, P_{HC}, all 58,282 observations were used in the modeling dataset. To model the passing probability of ASM CO given that ASM HC already passed, just the 55,455 observations that actually passed the ASM HC were used as the modeling dataset. Finally, to model the passing probability of ASM NX given that ASM HC and ASM CO both already passed, only the 55,182 observations that passed both the ASM HC and the ASM CO tests were used as the modeling dataset.

Table F-1. Summary of Model F Logistic Regressions

Model		Observations			Concordance (%)	Goodness of Fit Pr
Equation	Response	Pass	Fail	Total		
F-2	P_{HC}	55,455	2,827	58,282	82.6	0.0430
F-3	P_{CO} | HC Pass	55,182	273	55,455	78.4	0.5873
F-4	P_{NX} | HC, CO Pass	52,909	2,273	55,182	80.3	0.0011

For each of these three ASM pollutant passing probability models, we used the SAS logistic regression procedure with the stepwise option followed by several non-stepwise regression steps to determine which transformed RSD main effects and two-factor interactions had the greatest influence on the ASM passing probabilities. The resulting coefficients are given in Equations F-5, F-6, and F-7. Table F-1 shows the concordance and goodness of fit statistics for each of the three models. The concordance can be thought of as analogous to an r^2 expressed on a percent basis. Values closer to 100% mean that the model is predicting probability values that are in agreement with the ASM pass or fail results. The goodness of fit statistic indicates if the variables that are in the model are sufficient to describe all of the curvatures that are seen in the dataset. The table shows quite high values for concordance for all three models. The goodness of fit numbers show that there are small chances of lack of fit for HC and CO. However, there is a significant lack of fit for the NX model. On the other hand, when there are over 55,000 observations, the dataset has the statistical ability to see very small deviations from a good fit and, consequently, the size of the deviations may be of small practical importance.

We performed a check on the linearity and goodness of fit of the models by comparing the predicted probabilities with the fraction of observations that passed or failed. These comparisons can be made by examining Figures F-1, F-2, and F-3 for the training data and Figures F-5, F-6, and F-7 for the validation data. For the HC and CO passing probabilities, examination of Figures F-1, F-2, F-5, and F-6 show excellent agreement between measured and predicted values. For the NX model, Figures F-3 and F-7 show small deviations off the parity line in the region of passing probabilities from 0.8 to 0.9. This is the graphical representation of the lack of fit for the NX model seen in Table F-1. However, the graphs indicate that while the lack of fit is statistically significant, the NX model still has the ability to distinguish high from low passing probabilities since the curves in the figure are monotonically increasing within the scatter of the data points.

When the three models for the ASM mode pollutants are combined using Equation F-1, the overall ASM failure probability for the dataset can be calculated. Comparison of these calculated failing probabilities with the observed overall passing or failing observations is shown in Figures F-4 and F-8. These plots show that the Model F equations do a very good job at predicting the overall ASM failing probability. The influences of the small lack of fit in the NX model are evident in these plots by the deviation of the points off the parity line.

The following Model F equations can be used to calculate the overall ASM failure probability of a vehicle based on measured RSD emissions concentrations. None of the coefficients in these equations are vehicle-specific. The equations cannot be used to estimate average ASM emissions or average FTP emissions.

$$F_{\text{Overall Model F}} = 1 - (P_{HC}) * (P_{CO} \mid \text{HC Pass}) * (P_{NX} \mid \text{HC,CO Pass}) \qquad \text{[F-1]}$$

where:

$$P_{HC} = \exp(\text{arg2\_HCunc}) / (1 + \exp(\text{arg2\_HCunc})) \qquad \text{[F-2]}$$

$$P_{CO} \mid \text{HC Pass} = \exp(\text{arg2\_COcon}) / (1 + \exp(\text{arg2\_COcon})) \qquad \text{[F-3]}$$

$$P_{NX} \mid \text{HC,CO Pass} = \exp(\text{arg2\_NXcon}) / (1 + \exp(\text{arg2\_NXcon})) \qquad \text{[F-4]}$$

where:

$$\begin{aligned} \text{arg2\_HCunc} = \; & - 1.01450 \qquad \text{[F-5]} \\ & + 0.53095 * \text{arg\_tRSDHC} \\ & + 0.27750 * \text{arg\_tRSDCO} \\ & + 0.24847 * \text{arg\_tRSDNX} \\ & + 0.05439 * \text{arg\_tRSDCO} * \text{arg\_tRSDNX} \end{aligned}$$

$$\begin{aligned} \text{arg2\_COcon} = \; & + 1.93992 \qquad \text{[F-6]} \\ & + 0.00000 * \text{arg\_tRSDHC} \\ & + 0.56054 * \text{arg\_tRSDCO} \end{aligned}$$

– 0.01817 * arg_tRSDNX
+ 0.11661 * arg_tRSDCO * arg_tRSDNX

arg2_NXcon = + 0.24065 [F-7]
+ 0.00000 * arg_tRSDHC
+ 0.10572 * arg_tRSDCO
+ 0.42088 * arg_tRSDNX
+ 0.11013 * arg_tRSDCO * arg_tRSDNX

where:

P_{NX} | HC,CO Pass denotes the fractional conditional Passing probability of ASM NX (that is, both ASM2525 NX and ASM5015 NX pass) given that ASM HC (both modes) and ASM CO (both modes) have already passed.

arg_tRSDHC is calculated by Equation G-2
arg_tRSDCO is calculated by Equation G-7
arg_tRSDNX is calculated by Equation G-10

Table F-1. SAS Output for Equations F-2 and F-5

```
                         The SAS System                  13:23 Sunday, July 24, 2005   1

                     The LOGISTIC Procedure

                       Model Information

       Data Set                      WORK.HC
       Response Variable             hcres_pass
       Number of Response Levels     2
       Number of Observations        58282
       Link Function                 Logit
       Optimization Technique        Fisher's scoring


                        Response Profile

             Ordered     hcres_          Total
               Value     pass        Frequency

                   1            1        55455
                   2            0         2827

                   Model Convergence Status

       Convergence criterion (GCONV=1E-8) satisfied.


                     Model Fit Statistics

                                          Intercept
                             Intercept          and
          Criterion             Only     Covariates

          AIC              22626.043      18209.360
          SC               22635.016      18254.225
          -2 Log L         22624.043      18199.360

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                         The SAS System                  13:23 Sunday, July 24, 2005   2

                     The LOGISTIC Procedure

              Testing Global Null Hypothesis: BETA=0

  Test                 Chi-Square       DF     Pr > ChiSq

  Likelihood Ratio      4424.6834        4         <.0001
  Score                 5764.3578        4         <.0001
  Wald                  3681.0410        4         <.0001


              Analysis of Maximum Likelihood Estimates

                                              Standard
Parameter               DF     Estimate        Error    Chi-Square    Pr > ChiSq

Intercept                1      -1.0145       0.1550       42.8366        <.0001
arg_tRSDHC               1       0.5310       0.0242      483.0449        <.0001
arg_tRSDCO               1       0.2775       0.0460       36.3748        <.0001
arg_tRSDNX               1       0.2485       0.0548       20.5823        <.0001
arg_tRSDC*arg_tRSDNX     1       0.0544       0.0145       14.0133        0.0002


                      Odds Ratio Estimates

                         Point          95% Wald
       Effect          Estimate      Confidence Limits

       arg_tRSDHC         1.701       1.622       1.783


    Association of Predicted Probabilities and Observed Responses

       Percent Concordant         82.6    Somers' D    0.662
       Percent Discordant         16.4    Gamma        0.668
       Percent Tied                1.0    Tau-a        0.061
       Pairs                 156771285    c            0.831




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```

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

		hcres_pass = 1		hcres_pass = 0	
Group	Total	Observed	Expected	Observed	Expected
1	5828	4454	4439.81	1374	1388.19
2	5821	5238	5286.84	583	534.16
3	5822	5527	5528.96	295	293.04
4	5810	5630	5619.45	180	190.55
5	5846	5709	5711.89	137	134.11
6	5846	5767	5748.71	79	97.29
7	5885	5828	5812.42	57	72.58
8	5863	5818	5809.21	45	53.79
9	5759	5713	5719.74	46	39.26
10	5802	5771	5775.23	31	26.77

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
15.9564	8	0.0430

Table F-2. SAS Output for Equations F-3 and F-6

The LOGISTIC Procedure

Model Information

Data Set	WORK.CO
Response Variable	cores_pass
Number of Response Levels	2
Number of Observations	55455
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	cores_ pass	Total Frequency
1	1	55182
2	0	273

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	3448.019	3002.532
SC	3456.942	3038.225
-2 Log L	3446.019	2994.532

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	451.4873	3	<.0001
Score	576.8003	3	<.0001
Wald	379.6807	3	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	1.9399	0.4555	18.1400	<.0001
arg_tRSDCO	1	0.5605	0.1361	16.9707	<.0001
arg_tRSDNX	1	-0.0182	0.1471	0.0153	0.9017
arg_tRSDC*arg_tRSDNX	1	0.1166	0.0437	7.1201	0.0076

Association of Predicted Probabilities and Observed Responses

Percent Concordant	78.4	Somers' D	0.650
Percent Discordant	13.5	Gamma	0.707
Percent Tied	8.1	Tau-a	0.006
Pairs	15064686	c	0.825

Partition for the Hosmer and Lemeshow Test

Group	Total	cores_pass = 1 Observed	cores_pass = 1 Expected	cores_pass = 0 Observed	cores_pass = 0 Expected
1	5551	5413	5411.54	138	139.46
2	5570	5511	5518.34	59	51.66
3	5680	5651	5649.90	29	30.10
4	5319	5304	5301.11	15	17.89
5	5830	5820	5816.95	10	13.05
6	6022	6012	6012.95	10	9.05
7	6336	6333	6329.59	3	6.41

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

Group	Total	cores_pass = 1 Observed	cores_pass = 1 Expected	cores_pass = 0 Observed	cores_pass = 0 Expected
8	4696	4691	4692.62	5	3.38
9	6343	6339	6339.68	4	3.32
10	4108	4108	4106.59	0	1.41

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
6.5370	8	0.5873

Table F-3. SAS Output for Equations F-4 and F-7

The LOGISTIC Procedure

Model Information

Data Set	WORK.NX
Response Variable	nxres_pass
Number of Response Levels	2
Number of Observations	55182
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	nxres_ pass	Total Frequency
1	1	52909
2	0	2273

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	18952.692	16034.500
SC	18961.611	16070.173
-2 Log L	18950.692	16026.500

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	2924.1926	3	<.0001
Score	3263.3432	3	<.0001
Wald	2202.7751	3	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	0.2406	0.1833	1.7227	0.1893
arg_tRSDCO	1	0.1057	0.0460	5.2869	0.0215
arg_tRSDNX	1	0.4209	0.0697	36.4217	<.0001
arg_tRSDC*arg_tRSDNX	1	0.1101	0.0172	41.0902	<.0001

Association of Predicted Probabilities and Observed Responses

Percent Concordant	80.3	Somers' D	0.618
Percent Discordant	18.5	Gamma	0.625
Percent Tied	1.1	Tau-a	0.049
Pairs	120262157	c	0.809

Partition for the Hosmer and Lemeshow Test

		nxres_pass = 1		nxres_pass = 0	
Group	Total	Observed	Expected	Observed	Expected
1	5521	4585	4590.28	936	930.72
2	5516	4985	5025.98	531	490.02
3	5521	5244	5215.86	277	305.14
4	5503	5312	5306.85	191	196.15
5	5545	5432	5416.14	113	128.86
6	5538	5472	5453.14	66	84.86
7	5576	5527	5519.05	49	56.95

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

		nxres_pass = 1		nxres_pass = 0	
Group	Total	Observed	Expected	Observed	Expected
8	5499	5455	5460.35	44	38.65
9	5583	5545	5555.65	38	27.35
10	5380	5352	5362.86	28	17.14

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
25.8813	8	0.0011

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Figure F-1. Linearization Check for Equations F-2 and F-5 (Training Data)

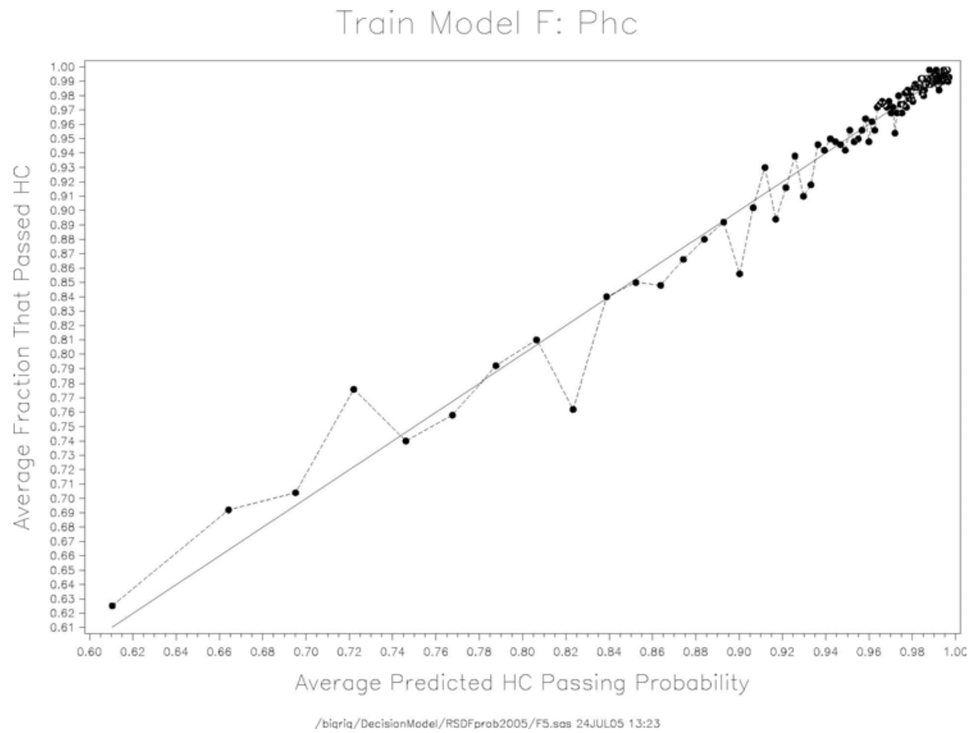


Figure F-2. Linearization Check for Equations F-3 and F-6 (Training Data)

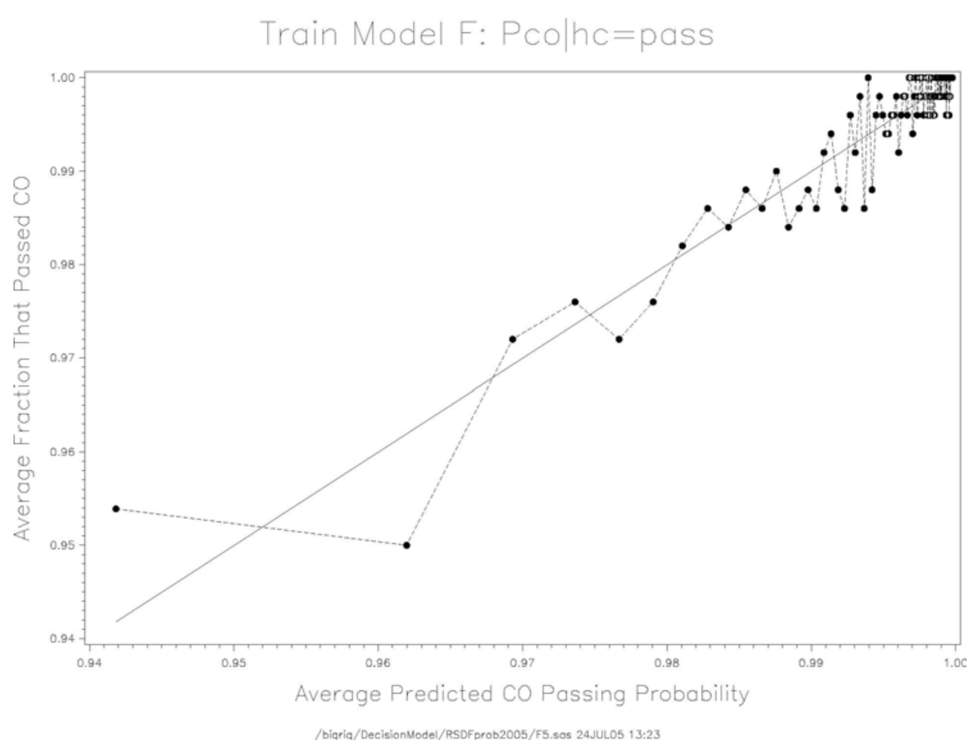


Figure F-3. Linearization Check for Equations F-4 and F-7 (Training Data)

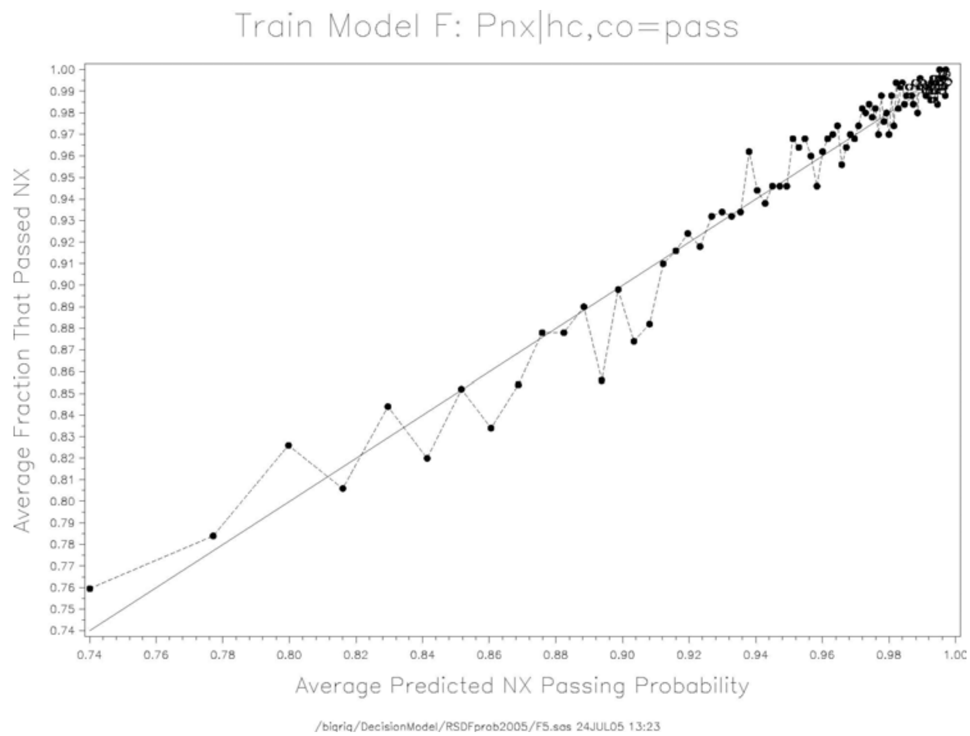


Figure F-4. Linearization Check for Equation F-1 (Training Data)

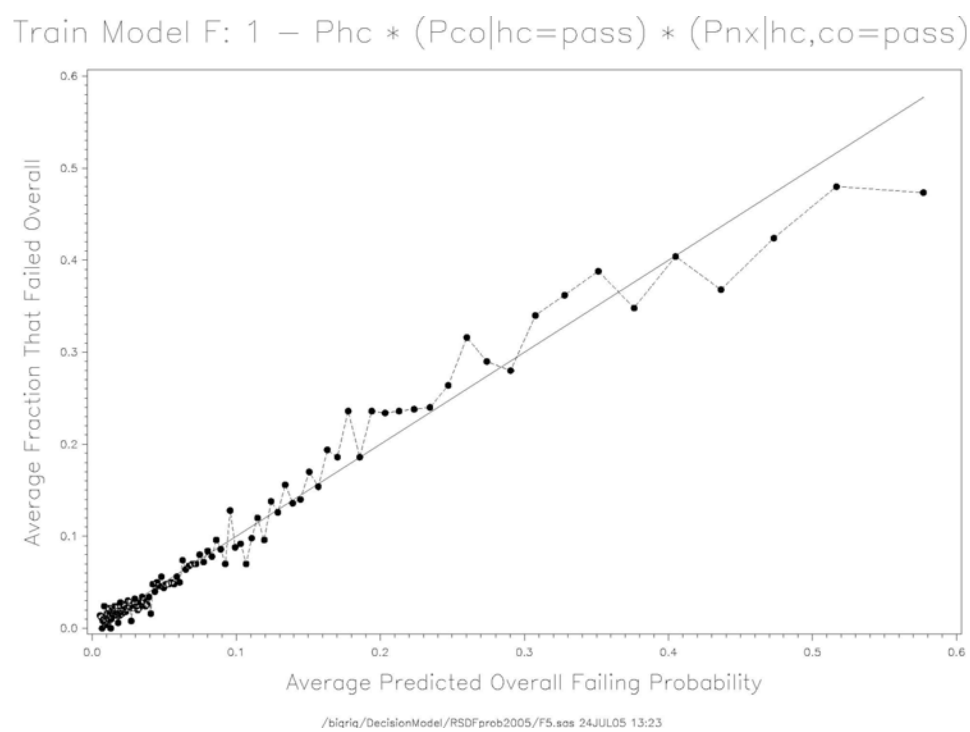


Figure F-5. Linearization Check for Equations F-2 and F-5 (Validation Data)

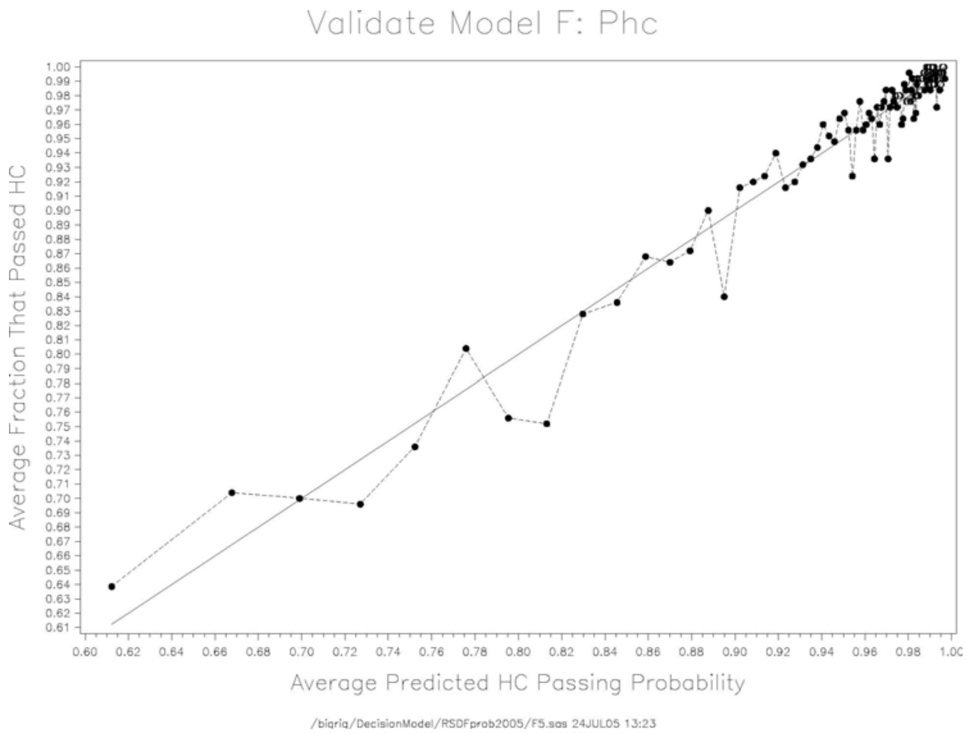


Figure F-6. Linearization Check for Equations F-3 and F-6 (Validation Data)

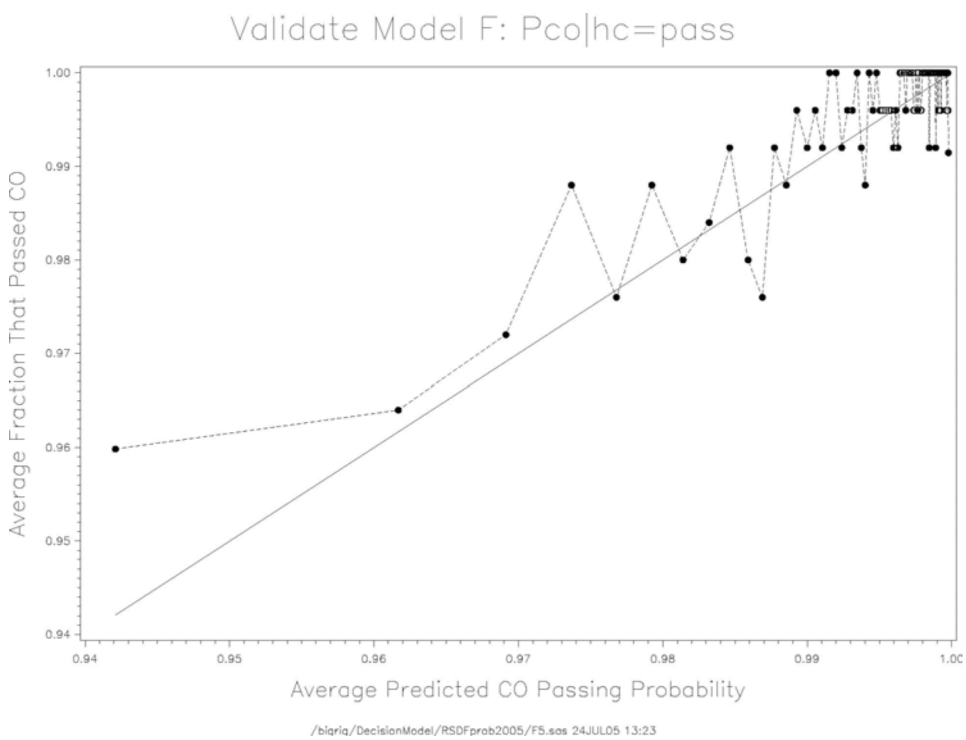


Figure F-7. Linearization Check for Equations F-4 and F-7 (Validation Data)

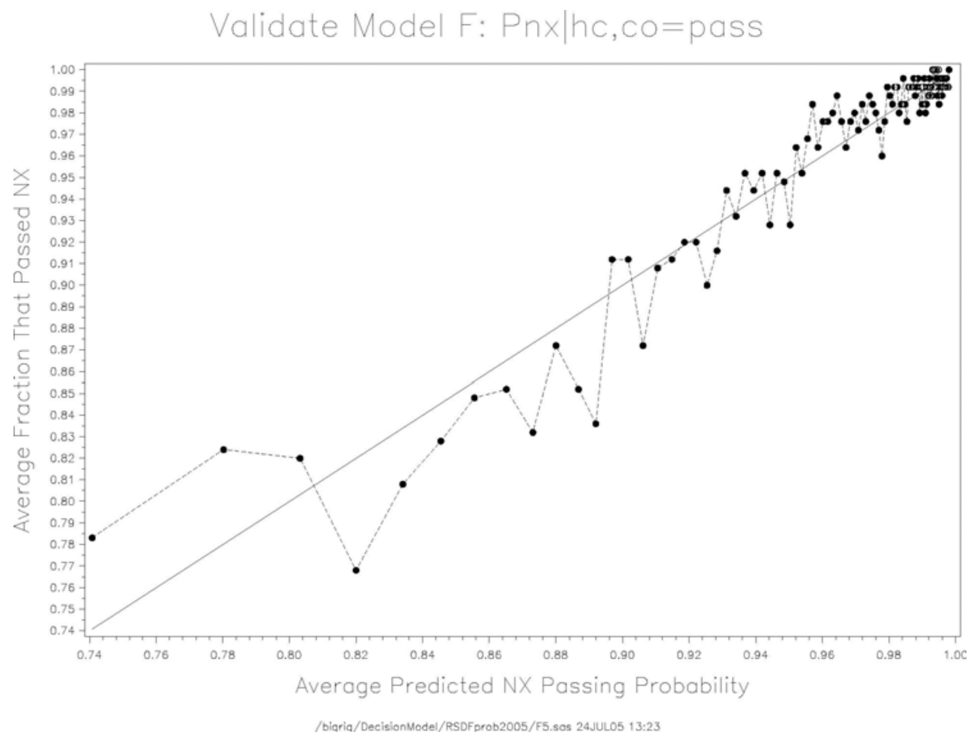
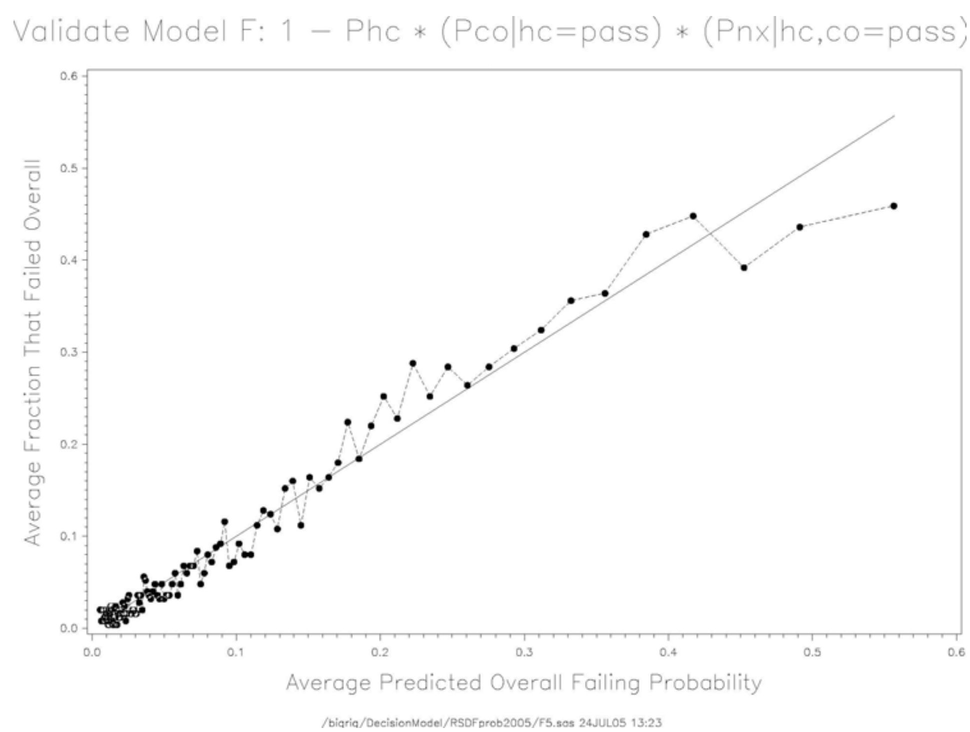


Figure F-8. Linearization Check for Equation F-1 (Validation Data)



Appendix G

RSD Linearizing Transformations

The first step was to determine the fractiles that corresponded to the RSD HC, RSD CO, and RSD NX measured concentrations.[41] The dataset used to make these calculations had 58,282 observations that contained valid RSD measurements that were in the acceptable VSP range. The observations also had complete initial-cycle ASM measurements in the VID at some time after the RSD measurements. Additionally, no other ASM measurements were between the time of the RSD measurement and the time of the initial cycle ASM inspection. These observations also represent 2/3 of all such pairs. We used 2/3 of the data to build the RSD transformation and the other 1/3 to validate the transformation. Separate transformations were used for each of the three types of RSD measurements. The RSD values for each measurement were sorted descending and assigned a relative fractile. The highest RSD reading had a relative fractile of 0.000017158 (=1/58282) and the highest fractile was 1.00000. The 58,282 RSD HC, RSD CO, and RSD NX measured concentrations and each of their fractile values were written to a SAS dataset for future use in ASM failure probability models that included measured RSD inputs.[42] RSD values at 0.01-fractile intervals are shown in Table G-1. The RSD values for all 58,282 observations are plotted in Figures G-1, G-2, and G-3.

The next step in the transformation of the RSD measurements was to find the transformation of the fractiles such that they are linear with the logit of the ASM pollutant Fprobs. For each of the three pollutants we searched for power transformations of the individual fractiles that would produce the best fit of the 58,282 pass/fail results for the initial-cycle ASM pollutant result that followed the RSD measurement. Logistic regression was used. For RSD CO, the 0.30 power produced the best fit; for RSD NX, the 0.58 power of the NX fractile produced the best fit. In the case of the RSD HC, the model was somewhat more complicated because of the segmented linear nature of the relationship between the RSD HC and the logit of the ASM HC Fprob. In that case, first the log of the HC fractile was taken. Then, logistic regression was used to find the best plus[43] functions that would best describe the non-linear relationship between the logit of the ASM HC failure probability and the log of the RSD HC fractile. The equations describe the relationships between the RSD fractiles and the ASM HC, CO, and NX passing probabilities.

The HC and NX models had no significant lack of fit; that is, the models fit the data well. The CO model had a significant lack of fit at the 98% confidence level. However, this level of lack of fit is acceptable given that the modeling dataset had 58,282 observations.

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[41] The program used to determine fractiles for the RSD concentrations is \bigrig\DecisionModel\RSDFprob2005\rankRSD.sas

[42] The relative RSD fractile look-up table is \bigrig\DecisionModel\RSDFprob2005\rsdranks.sas7bdat.

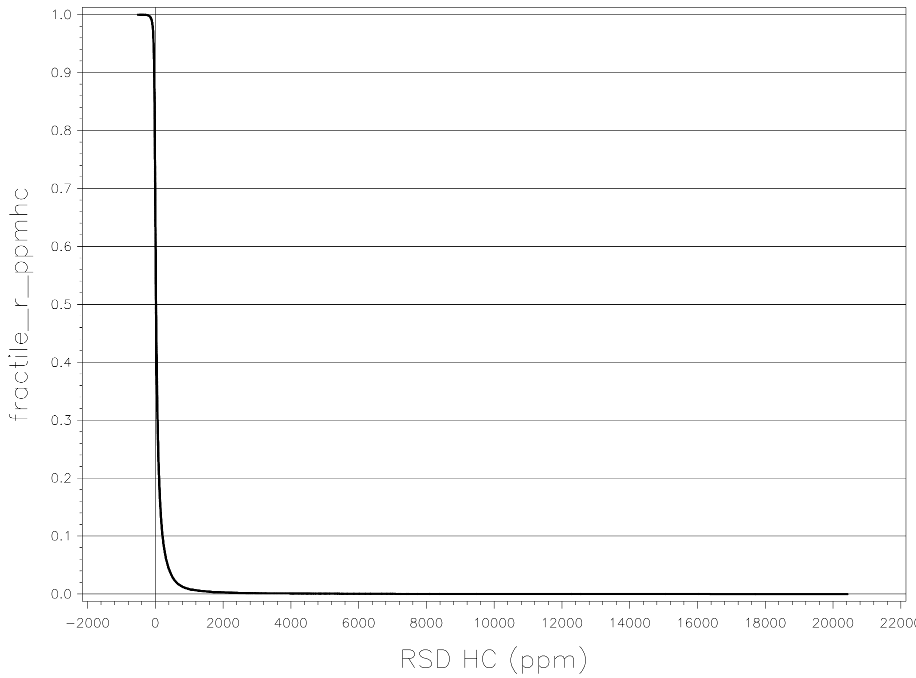
[43] Plus functions are functions that have values of zero below a constant value of the independent variable and have a non-zero functionality above the constant value. Equations G-3 and G-4 are examples.

Table G-1. Selected RSD Fractiles from the 58,282-Observation Dataset

Fractile	RSD HC (ppm)	RSD CO (%)	RSD NX (ppm)
1.00	-513.88	-0.2969	-2158.45
0.99	-105.06	-0.0716	-138.84
0.98	-77.39	-0.0458	-90.30
0.97	-63.73	-0.0312	-71.07
0.96	-55.23	-0.0217	-57.98
0.95	-48.91	-0.0159	-48.63
0.94	-44.38	-0.0115	-41.30
0.93	-40.13	-0.0079	-35.38
0.92	-36.60	-0.0051	-30.88
0.91	-33.53	-0.0033	-26.93
0.90	-30.88	-0.0017	-23.10
0.89	-28.53	-0.0003	-19.78
0.88	-26.30	0.0009	-16.85
0.87	-24.31	0.0020	-14.08
0.86	-22.58	0.0030	-11.75
0.85	-20.90	0.0039	-9.48
0.84	-19.26	0.0048	-7.50
0.83	-17.86	0.0057	-5.57
0.82	-16.53	0.0065	-3.58
0.81	-15.13	0.0073	-1.82
0.80	-13.81	0.0081	0.01
0.79	-12.61	0.0089	1.70
0.78	-11.44	0.0097	3.33
0.77	-10.32	0.0106	4.97
0.76	-9.22	0.0113	6.67
0.75	-8.13	0.0121	8.39
0.74	-7.08	0.0129	10.20
0.73	-5.99	0.0137	12.00
0.72	-4.90	0.0146	13.77
0.71	-3.86	0.0155	15.70
0.70	-2.83	0.0164	17.67
0.69	-1.82	0.0173	19.59
0.68	-0.77	0.0182	21.69
0.67	0.26	0.0191	23.89
0.66	1.40	0.0201	26.04
0.65	2.48	0.0212	28.51
0.64	3.63	0.0222	31.15
0.63	4.78	0.0234	33.78
0.62	5.79	0.0246	36.52
0.61	6.97	0.0259	39.45
0.60	8.18	0.0272	42.30
0.59	9.45	0.0286	45.61
0.58	10.77	0.0301	48.91
0.57	11.99	0.0316	52.29
0.56	13.39	0.0332	56.06
0.55	14.71	0.0350	59.91
0.54	16.13	0.0368	63.76
0.53	17.65	0.0386	67.68
0.52	19.13	0.0405	72.26
0.51	20.69	0.0423	76.66

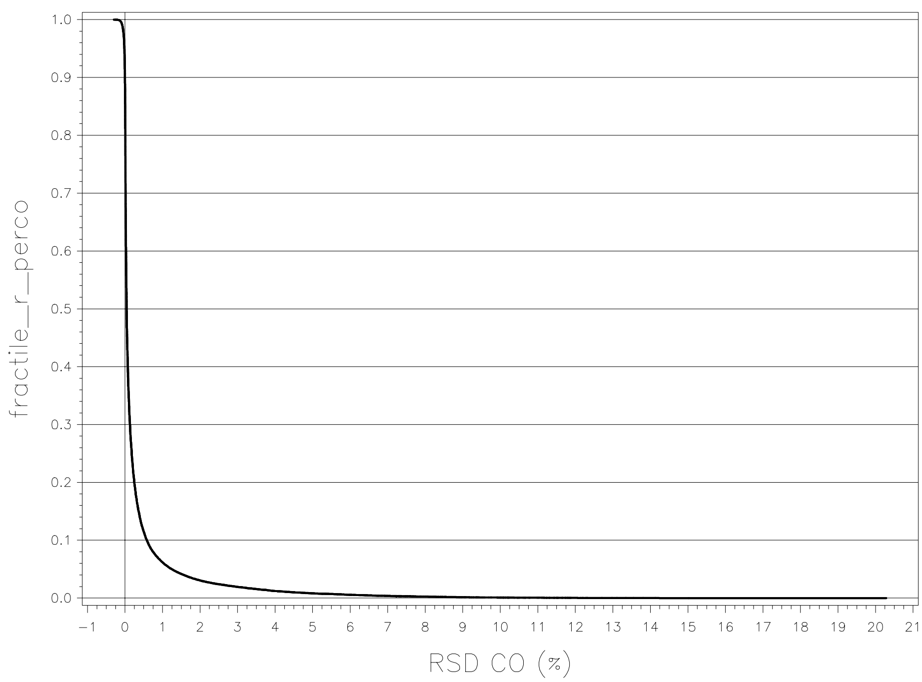
Fractile	RSD HC (ppm)	RSD CO (%)	RSD NX (ppm)
0.50	22.30	0.0445	81.40
0.49	23.96	0.0467	86.55
0.48	25.69	0.0490	92.06
0.47	27.51	0.0516	97.70
0.46	29.29	0.0542	104.13
0.45	31.03	0.0570	110.48
0.44	32.94	0.0600	117.60
0.43	34.82	0.0635	124.44
0.42	36.87	0.0671	132.18
0.41	38.89	0.0709	140.62
0.40	41.19	0.0749	149.89
0.39	43.30	0.0791	158.81
0.38	45.60	0.0837	168.51
0.37	47.98	0.0880	179.73
0.36	50.60	0.0933	190.47
0.35	53.13	0.0993	201.84
0.34	55.71	0.1049	213.63
0.33	58.46	0.1111	226.37
0.32	61.56	0.1180	239.98
0.31	64.46	0.1248	254.37
0.30	67.57	0.1325	271.98
0.29	70.83	0.1406	293.10
0.28	74.42	0.1492	311.79
0.27	77.98	0.1590	328.06
0.26	82.02	0.1694	346.49
0.25	86.24	0.1803	366.86
0.24	90.58	0.1911	387.79
0.23	95.47	0.2036	411.15
0.22	101.09	0.2174	435.82
0.21	106.69	0.2329	460.42
0.20	112.20	0.2498	487.23
0.19	118.52	0.2682	517.39
0.18	125.88	0.2865	548.63
0.17	133.70	0.3100	580.68
0.16	141.69	0.3352	619.35
0.15	150.90	0.3637	660.37
0.14	160.45	0.3945	702.00
0.13	172.61	0.4292	749.45
0.12	184.72	0.4744	798.55
0.11	199.53	0.5246	853.02
0.10	215.35	0.5814	918.35
0.09	235.75	0.6525	991.30
0.08	258.29	0.7463	1068.93
0.07	288.12	0.8732	1166.04
0.06	320.39	1.0321	1280.02
0.05	365.96	1.2482	1412.42
0.04	423.11	1.5691	1585.27
0.03	501.42	2.0354	1805.65
0.02	623.00	2.9311	2115.89
0.01	920.06	4.5072	2590.70
0.00	20425.55	20.2821	7763.39

Figure G-1. RSD HC Fractile Values



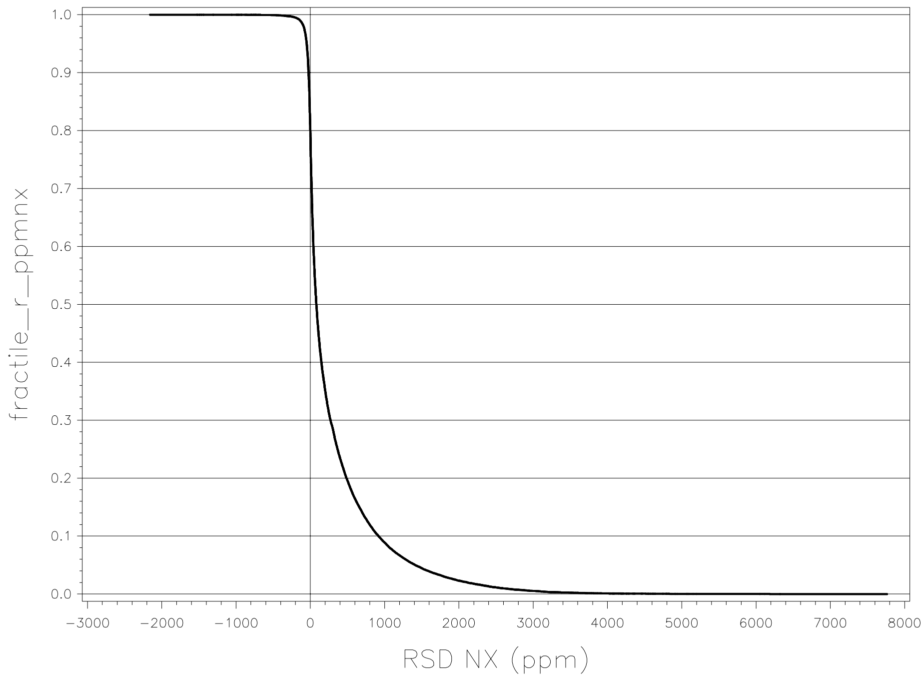
/bigrig/DecisionModel/RSDFprob2005/rankRSD graphs.sas 03NOV05 15:1

Figure G-2. RSD CO Fractile Values



/bigrig/DecisionModel/RSDFprob2005/rankRSD graphs.sas 03NOV05 15:1

Figure G-3. RSD NX Fractile Values



/bigrig/DecisionModel/RSDFprob2005/rankRSD_graphs.sas 03NOV05 15:1

Figures G-4, G-5, and G-6 show the linear relationship for ASM HC, CO and NX passing probabilities for the 58,282 observations in the training dataset. Figures G-7, G-8, and G-9 show the same relationship for the 28,743 observations in the validation dataset, whose observations have not been used for ranking or model building. For all six plots, the scatter in the data points around the parity line is the expected size. For the training plots, each data point shows the average value for 500 observations; for the validation plots every data point shows the average value for 250 observations.

Figure G-4. Linearization Check for Equation G-1 (Training Data)

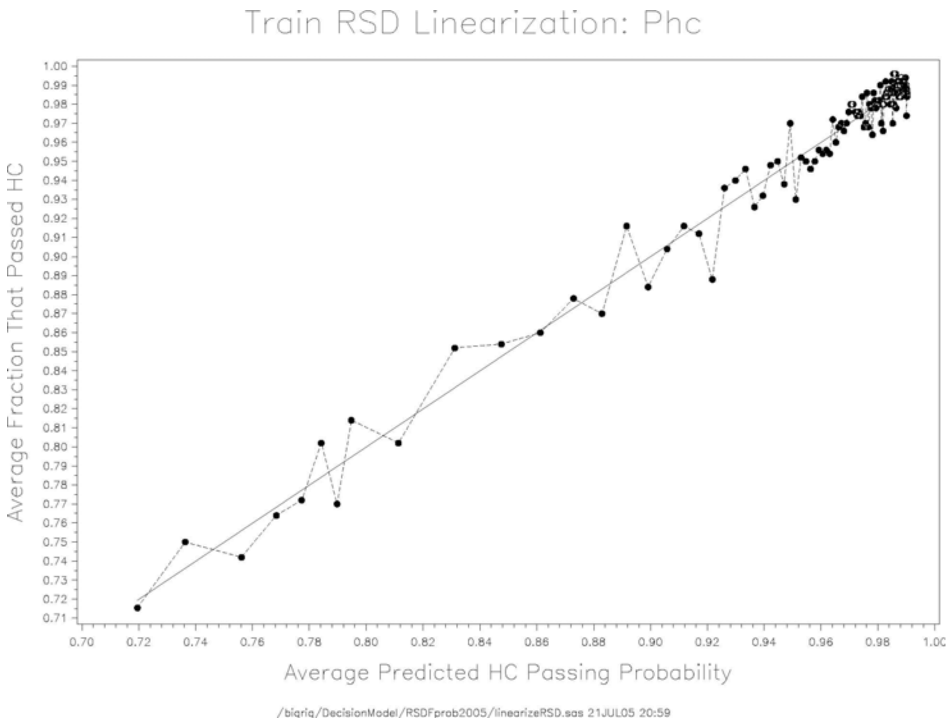


Figure G-5. Linearization Check for Equation G-6 (Training Data)

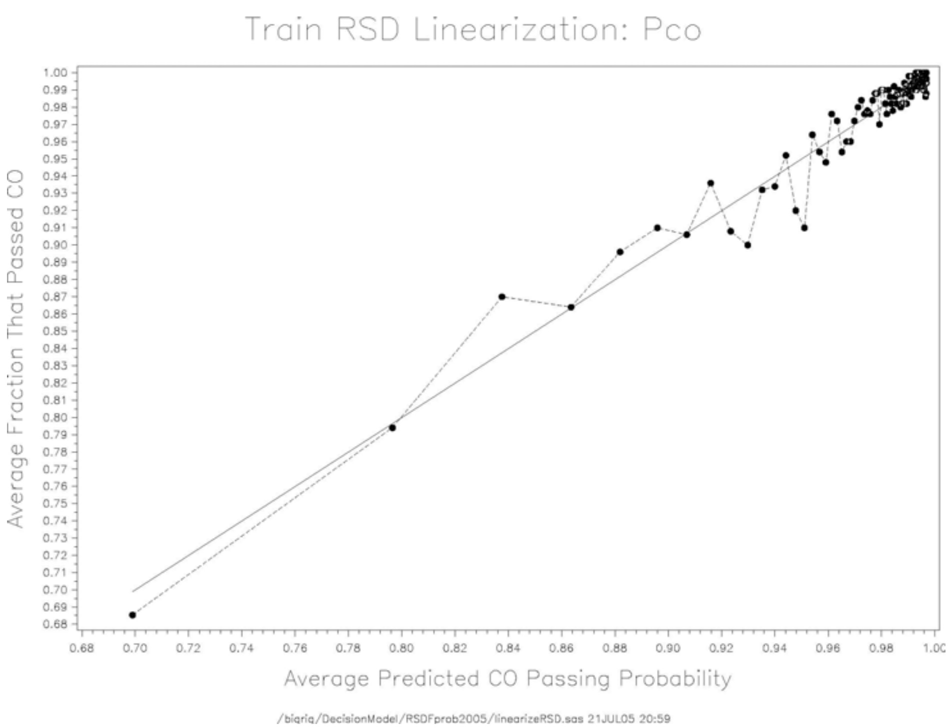


Figure G-6. Linearization Check for Equation G-9 (Training Data)

Figure G-7. Linearization Check for Equation G-1 (Validation Data)

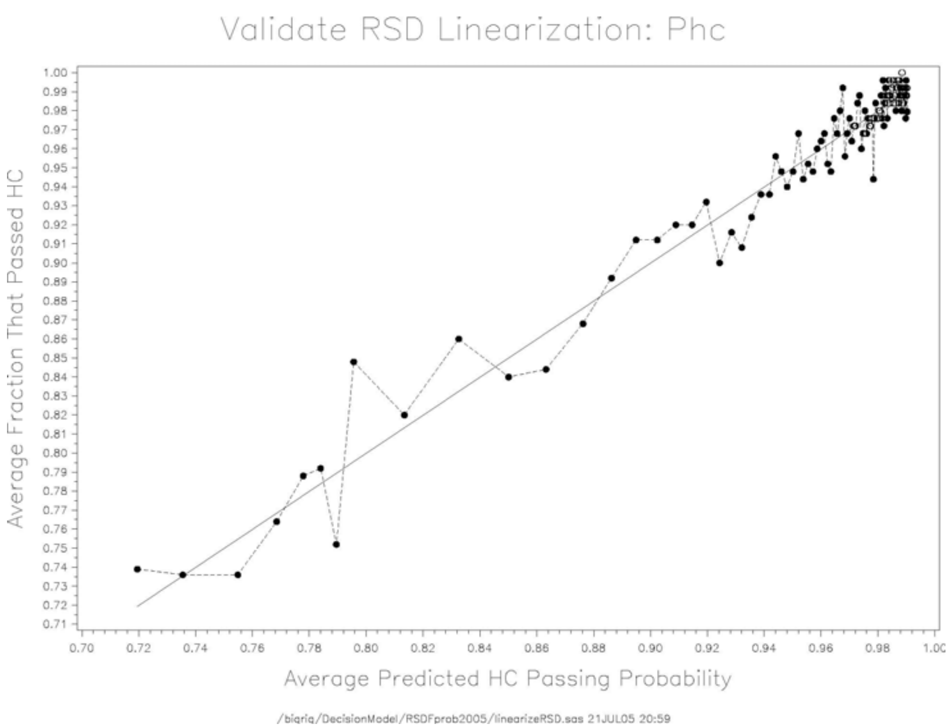


Figure G-8. Linearization Check for Equation G-6 (Validation Data)

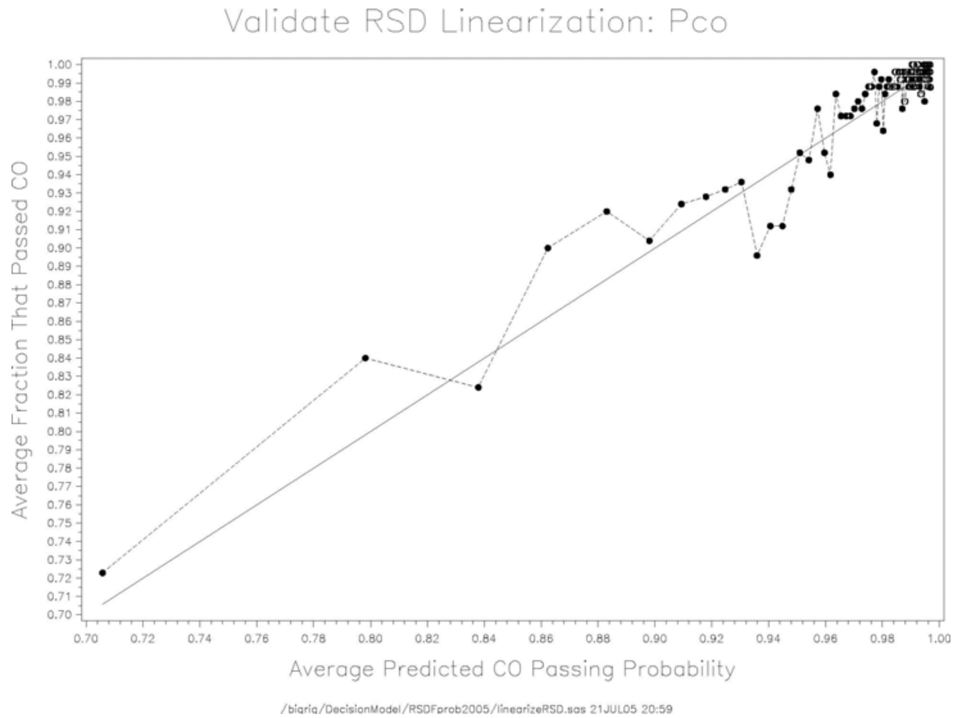
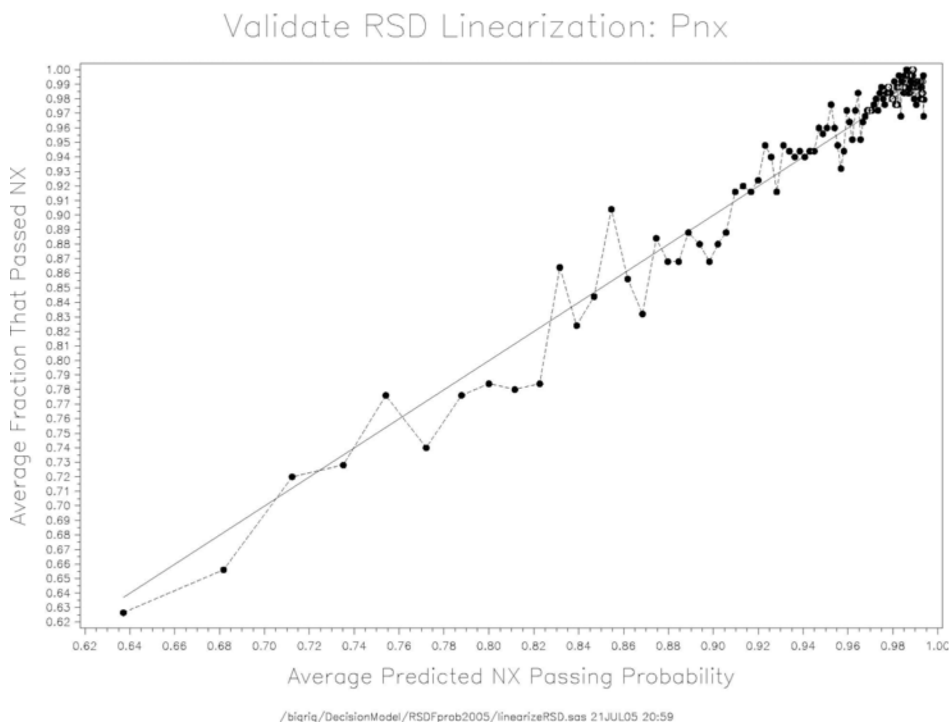


Figure G-9. Linearization Check for Equation G-9 (Validation Data)



The following equations are used in conjunction with the RSD fractile look-up table to transform measured RSD concentrations to values that are linear with the logits of the ASM pollutant failure probabilities.

P_{HC} = exp(arg_tRSDHC) / (1 + exp(arg_tRSDHC)) [G-1]

where:

arg_tRSDHC = 0.9421 + (1.0132) * x27 + (0.1995) * x48 [G-2]

x27 = 0, for $x \leq -2.7$ [G-3]
= x + 2.7, for $x > -2.7$

x48 = 0, for $x \leq -4.8$ [G-4]
= x + 4.8, for $x > -4.8$

x = ln(fractile_r_ppmhc) [G-5]

fractile_r_ppmhc is the fractile value corresponding to the measured RSD HC (ppm) as looked up in the fractile reference table. High RSD values have low fractile values.

P_{CO} = exp(arg_tRSDCO) / (1 + exp(arg_tRSDCO)) [G-6]

where:

arg_tRSDCO = -0.2621 + (6.0382) * t30_cofractile [G-7]

t30_cofractile = fractile_r_perco **0.30 [G-8]

fractile_r_perco is the fractile value corresponding to the measured RSD CO (%) as looked up in the fractile reference table. High RSD values have low fractile values.

P_{NX} = exp(arg_tRSDNX) / (1 + exp(arg_tRSDNX)) [G-9]

where:

arg_tRSDNX = 0.3814 + (4.7166) * t58_nxfractile [G-10]

t58_nxfractile = fractile_r_ppmnx **0.58 [G-11]

fractile_r_ppmnx is the fractile value corresponding to the measured RSD NX (ppm) as looked up in the fractile reference table. High RSD values have low fractile values.

Table G-2. SAS Output for Equation G-2

```
                     The SAS System                    20:59 Thursday, July 21, 2005   1

                 The LOGISTIC Procedure

                   Model Information

        Data Set                      WORK.TRAIN
        Response Variable             hcres_pass
        Number of Response Levels     2
        Number of Observations        58282
        Link Function                 Logit
        Optimization Technique        Fisher's scoring


                    Response Profile

              Ordered     hcres_          Total
                Value     pass        Frequency

                    1            1        55455
                    2            0         2827


                Model Convergence Status

        Convergence criterion (GCONV=1E-8) satisfied.


                 Model Fit Statistics

                                        Intercept
                           Intercept          and
           Criterion         Only       Covariates

           AIC           22626.043      19273.375
           SC            22635.016      19300.294
           -2 Log L      22624.043      19267.375
```

/bigrig/DecisionModel/RSDFprob2005/linearizeRSD.sas 21JUL05 20:59

```
                     The SAS System                    20:59 Thursday, July 21, 2005   2

                 The LOGISTIC Procedure

           Testing Global Null Hypothesis: BETA=0

      Test                 Chi-Square       DF     Pr > ChiSq

      Likelihood Ratio      3356.6679        2         <.0001
      Score                 4388.8082        2         <.0001
      Wald                  3111.7049        2         <.0001


          Analysis of Maximum Likelihood Estimates

                                    Standard
Parameter    DF    Estimate        Error    Chi-Square    Pr > ChiSq

Intercept     1      0.9421       0.0704      179.0257        <.0001
x27           1      1.0132       0.0596      288.7924        <.0001
x48           1      0.1995       0.0416       22.9548        <.0001


                  Odds Ratio Estimates

                       Point          95% Wald
          Effect    Estimate      Confidence Limits

          x27          2.754       2.451       3.096
          x48          1.221       1.125       1.325


   Association of Predicted Probabilities and Observed Responses

       Percent Concordant         78.1    Somers' D    0.579
       Percent Discordant         20.2    Gamma        0.589
       Percent Tied                1.7    Tau-a        0.053
       Pairs                 156771285    c            0.789
```

/bigrig/DecisionModel/RSDFprob2005/linearizeRSD.sas 21JUL05 20:59

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

		hcres_pass = 1		hcres_pass = 0	
Group	Total	Observed	Expected	Observed	Expected
1	5831	4604	4592.63	1227	1238.37
2	5827	5287	5290.11	540	536.89
3	5819	5504	5525.65	315	293.35
4	5856	5663	5657.92	193	198.08
5	5841	5696	5694.57	145	146.43
6	5897	5771	5780.75	126	116.25
7	5713	5633	5620.65	80	92.35
8	5915	5840	5834.36	75	80.64
9	5644	5593	5577.68	51	66.32
10	5939	5864	5877.86	75	61.14

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
11.6530	8	0.1674

Table G-3. SAS Output for Equation G-7

The LOGISTIC Procedure

Model Information

Data Set	WORK.TRAIN
Response Variable	cores_pass
Number of Response Levels	2
Number of Observations	58282
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	cores_ pass	Total Frequency
1	1	56854
2	0	1428

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	13415.679	11121.947
SC	13424.652	11139.893
-2 Log L	13413.679	11117.947

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	2295.7319	1	<.0001
Score	2882.8199	1	<.0001
Wald	2143.5250	1	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	-0.2621	0.0750	12.2254	0.0005
t30_cofractile	1	6.0382	0.1304	2143.5250	<.0001

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
t30_cofractile	419.131	324.591	541.206

Association of Predicted Probabilities and Observed Responses

Percent Concordant	80.6	Somers' D	0.636
Percent Discordant	17.0	Gamma	0.651
Percent Tied	2.4	Tau-a	0.030
Pairs	81187512	c	0.818

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

		cores_pass = 1		cores_pass = 0	
Group	Total	Observed	Expected	Observed	Expected
1	5824	5102	5097.36	722	726.64
2	5826	5547	5580.09	279	245.91
3	5801	5693	5661.53	108	139.47
4	5885	5795	5792.09	90	92.91
5	5821	5752	5755.84	69	65.16
6	5788	5742	5739.57	46	48.43
7	5921	5890	5882.74	31	38.26
8	6114	6085	6082.83	29	31.17
9	5895	5867	5870.74	28	24.26
10	5407	5381	5388.51	26	18.49

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
17.5855	8	0.0246

Table G-4. SAS Output for Equation G-10

The LOGISTIC Procedure

Model Information

Data Set	WORK.TRAIN
Response Variable	nxres_pass
Number of Response Levels	2
Number of Observations	58282
Link Function	Logit
Optimization Technique	Fisher's scoring

Response Profile

Ordered Value	nxres_ pass	Total Frequency
1	1	54786
2	0	3496

Model Convergence Status

Convergence criterion (GCONV=1E-8) satisfied.

Model Fit Statistics

Criterion	Intercept Only	Intercept and Covariates
AIC	26453.179	22173.091
SC	26462.152	22191.037
-2 Log L	26451.179	22169.091

The LOGISTIC Procedure

Testing Global Null Hypothesis: BETA=0

Test	Chi-Square	DF	Pr > ChiSq
Likelihood Ratio	4282.0881	1	<.0001
Score	4419.1224	1	<.0001
Wald	3458.6832	1	<.0001

Analysis of Maximum Likelihood Estimates

Parameter	DF	Estimate	Standard Error	Chi-Square	Pr > ChiSq
Intercept	1	0.3814	0.0360	112.3521	<.0001
t58_nxfractile	1	4.7166	0.0802	3458.6832	<.0001

Odds Ratio Estimates

Effect	Point Estimate	95% Wald Confidence Limits	
t58_nxfractile	111.793	95.532	130.822

Association of Predicted Probabilities and Observed Responses

Percent Concordant	79.9	Somers' D	0.607
Percent Discordant	19.2	Gamma	0.613
Percent Tied	0.9	Tau-a	0.068
Pairs	191531856	c	0.804

The LOGISTIC Procedure

Partition for the Hosmer and Lemeshow Test

		nxres_pass = 1		nxres_pass = 0	
Group	Total	Observed	Expected	Observed	Expected
1	5829	4424	4419.10	1405	1409.90
2	5835	5067	5096.80	768	738.20
3	5820	5391	5370.26	429	449.74
4	5842	5555	5547.99	287	294.01
5	5823	5609	5624.04	214	198.96
6	5862	5731	5721.85	131	140.15
7	5845	5756	5744.90	89	100.10
8	5844	5780	5770.85	64	73.15
9	5876	5818	5821.39	58	54.61
10	5706	5655	5665.95	51	40.05

Hosmer and Lemeshow Goodness-of-Fit Test

Chi-Square	DF	Pr > ChiSq
10.0380	8	0.2624

Appendix H

Review of Logistic Regression

Logistic regression is a standard statistical modeling technique that is used to predict the probability of the occurrence of discrete response variable levels. In this study, we are interested in predicting the probability of a vehicle having a pass for a given I/M emissions inspection result. The form of the logistic regression model is:

$$P = \frac{\exp(\arg)}{1 + \exp(\arg)}$$

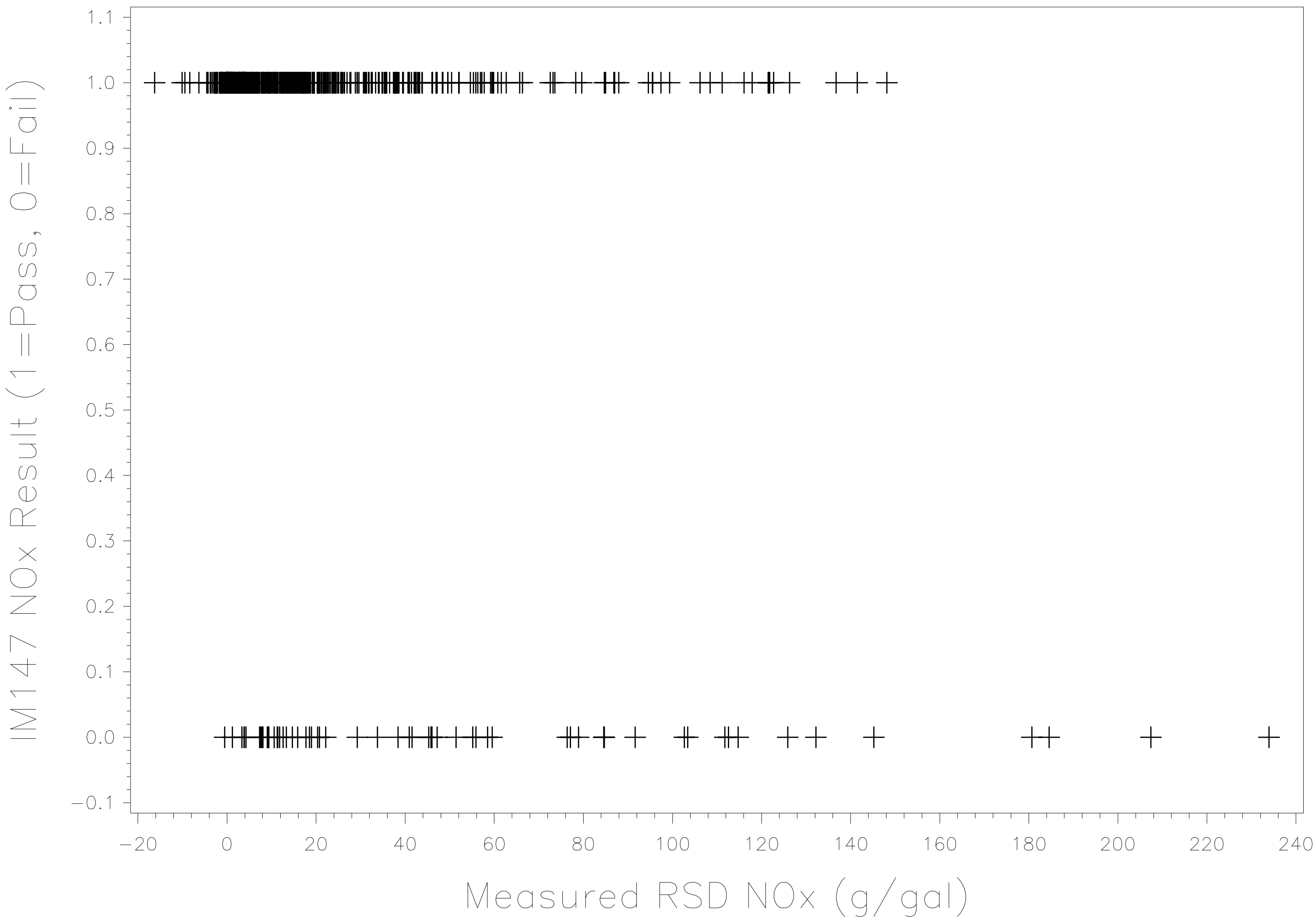
where: P is the probability of passing the emissions test, and
arg is a function of the inputs to the model.

Examination of the functional form shows that when *arg* approaches minus infinity, P approaches zero and when *arg* approaches positive infinity, P approaches 1. When *arg* equals zero, P equals 0.5.

The logistic procedure in SAS uses a training dataset made up of values for the inputs and discrete values for the response variable, which is the emissions test pass/fail result for this study. In this study, pass was designated with a value of 1 and fail was designated with a value of 0. The modeling effort focuses on determining the functional form of the inputs that describe *arg* such that the passes and fails of the response variable in the training dataset are fit optimally. As with any sort of regression, better models are those that fit the training data and can also generalize well so that the predicted results for independent validation set agree with the actual pass/fail results.

An example problem will serve to familiarize the reader with logistic regression. Figure H-1 shows a plot of experimental results for a set of vehicles that have had an IM147 NX measurement and a remote sensing NX measurement. All of the vehicles in the figure have the same IM147 NX cutpoint of 2.5 g/mile. The vertical axis shows the pass/fail result for the IM147 NX and the horizontal axis shows the measured RSD NX in g/gal. Because the response variable is simply the IM147 NX pass or fail result, the plot shows a line of passing symbols at 1 and a line of failing symbols at 0. Examination of the symbols at 1 indicates that the measured RSD NX values are positively skewed since the density of points is greater at low RSD NX values. The same observation can be made about the failing vehicle RSD NX values. While the RSD NX values for failing vehicles extend to higher levels than for the passing vehicles, it is clear that the measured RSD NX value does not provide sufficient information to

Figure H-1. Matched Test Results for 2.5 g NX /mile Cutpoint



roadhog/arizona/profiling/pred147t.sas

say with certainty that the vehicle with a given RSD NX value will be a passing or failing IM147 vehicle when tested. That is, the two distributions of measured RSD NX for the passing and failing vehicles overlap to a substantial degree. Nevertheless, the plot causes us to suspect that measured RSD NX values carry some important information about whether a vehicle will pass or fail the IM147 NX test.

This suspicion is quantified in Figure H-2. In this figure, vertical dashed lines have split the measured RSD NX axis into bins with a width of 20 g/gal. Each bin has a number of passing and failing IM147 NX results. If we count the number of passing vehicles and the number of failing vehicles in each bin, the probability that a vehicle with an RSD NX value in a bin can be estimated from the ratio of the number of passing vehicles to the total number of vehicles in each bin. For example, for the RSD NX bin from 140 to 160 g/gal, there were 2 passing vehicles and 1 failing vehicle. This means that the probability of a vehicle that has a measured RSD NX between 140 and 160 g/gal would be approximately 2/(2+1) or 67%. Such values for each of the bins are plotted in the figure as the dots. The trend of these dots shows that as the measured RSD NX increases, the probability of a vehicle passing the IM147 test decreases.

While the consideration of the number of passing and failing vehicles in each bin is useful for visualizing the effect, the formal statistical regression technique known as logistic regression provides greater usefulness for analyzing the data. The result of the SAS logistic regression procedure is shown in Figure H-3 as the sigmoidal curved line. The figure shows that the curved line passes through the field of dots in the figure. The equation for this curved line is:

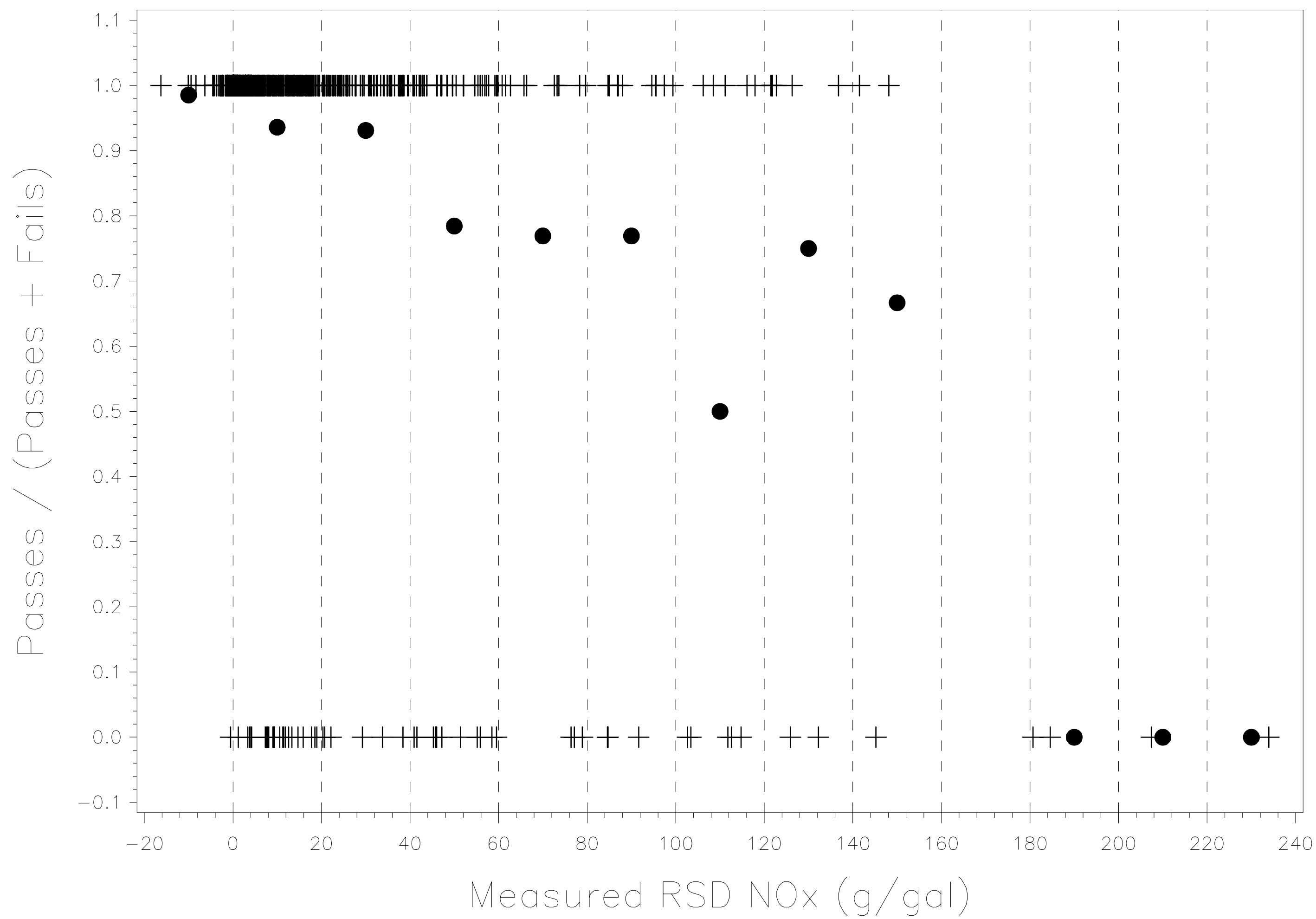
$$P = \frac{\exp\,(a + b * \text{RSD NX})}{1 + \exp\,(a + b * \text{RSD NX})}$$

where: $a = 2.7$
$b = -0.02$

This equation can be used to predict the probability of an IM147 NX pass given the measured value of an RSD NX at any value including values for which no observations were made, for example, between 160 and 180 g/gal.

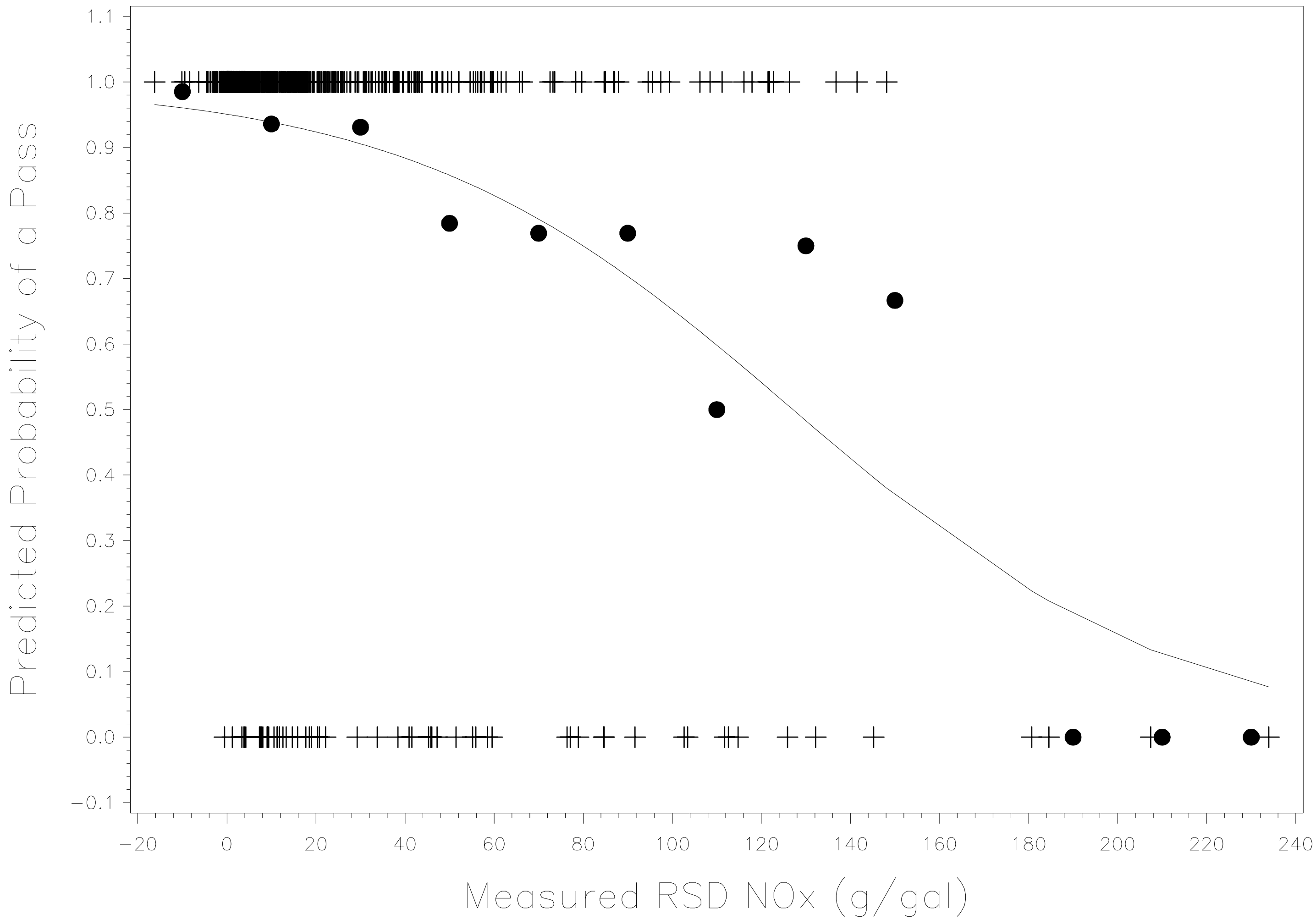
Clearly, the uncertainty in the probability estimate is greater where the data is more sparse in the training dataset. In the case of this example, this would be at higher measured RSD NX values. This greater uncertainty is also reflected in the increased scatter of the average pass ratios that were calculated and displayed on the figures as dots for the higher RSD NX values.

Figure H-2. Ratio of Passes to all Tests



roadhog/arizona/profiling/pred147t.sas

Figure H-3. Regression Prediction of Pass Probability



roadhog/arizona/profiling/pred147t.sas

From an experimental data collection perspective, the uncertainty in the pass probabilities at high RSD NX values could be reduced through the use of stratified sampling. However, stratified sampling must be performed in an appropriate manner to avoid the possibility of creating a bias in the dataset.

For example, a bias would definitely be created if vehicles that failed the IM147 NX test were selected preferentially. Such vehicle selection would cause a larger number of symbols in Figure H-3 having values of zero for the IM147 NX pass/fail result out of proportion to the passing vehicles with symbols at 1. This would cause the bin ratios of passing to total vehicles within each bin and the logistic regression curve to shift to lower predicted probability values. The use of the resulting model would under-estimate the true probability of vehicles passing the IM147 NX test.

An acceptable method for stratifying the data collection would be to use data from vehicles selected based on their measured RSD NX values. For example, suppose the test program preferentially measured the RSD and IM147 NX results for vehicles that had measured RSD NX results greater than 100 g/gal. In this case, the number of passing and failing IM147 NX vehicles would increase together. The resulting logistic regression curve would be in approximately the same location as if stratified sampling were not used. However, at high values of RSD NX the uncertainty in the predicted probability of passing IM147 tests would be reduced because of a larger number of total vehicles in each RSD NX bin.

While the ratio of passes to total tests in each of several bins of an input variable can be used to estimate predicted probability of a passing test, the use of the statistical logistic regression technique has a number of advantages. One of the most important of these is that a number of input variables can be considered at a time so that a better combination of input variables for *arg* can be discovered. This can result in an improved model and improved values for predicted probabilities. In the SAS logistic regression procedure, a stepwise input variable selection technique is available to evaluate and select competing input variables. Another big advantage of the logistic regression procedure is that a number of statistics are output to evaluate the quality of the resulting logistic regression model. These are summarized briefly below.

Chi-Square – This statistic is a measure of the influence of an input variable on the probability of the outcome of the response variable. Inputs with the highest chi-square values are more influential than those with low chi-square values.

Significance of Input P-Value – For each of the input variables in a logistic regression model, this P-value gives the level of significance of the input value on the logistic regression model. We are 95% confident that a variable with a P-value less than 0.05 has a significant effect on the predicted probability. We want to find input variables that have P-values that are as close as possible to zero. These values would have a very small chance that they have an influence on the response variable by chance alone.

Concordance – Concordance is a statistic for a logistic regression that evaluates the agreement between the predicted probabilities of a model and the pass and fail values of the individual observations in the training set. Concordance can have a value from 0 to 100%. If the predicted probabilities completely agree with the pass and fail values of the response variable, then the concordance is 100%.

Hosmer-Lemeshow Lack of Fit – This lack of fit test determines whether the input variables used in the model describe the pass/fail response variable sufficiently well with the functionality used for the input variables. The procedure outputs a P-value for lack of fit. P-values less than 0.05 indicate 95% confidence that the input variable functionality could be improved and that the functionality which is used in the current model does not describe all of the functionality that the variables could describe. A well fitting model will have a lack of fit P-value between 0.05 and 1.00.

Odds Ratio of the Input – An odds ratio is provided for each of the input variables in a logistic regression model and indicates the direction of the influence of the input variable on the predicted probability. If the odds ratio is less than 1, then an increase in that input variable will decrease the probability of the output from occurring. If the odds ratio is greater than 1, then an increase in that input variable will increase the probability of the output from occurring.

The goal of the development of logistic regression models is to find a short list of input variables that produces a model with high concordance, no significant lack of fit, and for which the model inputs are all statistically significant and have odds ratios that indicate the direction of their influence on the output is in a direction that makes sense. Just as in other types of statistical regression, the inclusion of numerous additional inputs can increase the fit of the model to the training data. However, this should be avoided otherwise the ability of the model to generalize for independent datasets may be compromised.

Appendix I

Review of Combining Probabilities

In this report six separate models will be built to predict the probability of passing ASM HC2525, HC5015, CO2525, CO5015, NX2525, and NX5015, and then the predicted probabilities from these six models will be combined to calculate the predicted overall probability of failing the overall ASM test. The alternative approach would have been to build a single model that predicts the overall probability of failing any one of the six ASM tests. However, we expect that such an overall model would require many inputs to include information about each of the pollutants. For example, the overall model would require inputs of RSD HC, RSD CO, RSD NX, all six ASM cutpoints, and all six ASM Fprobs. By building six separate models, we reduce the number of required inputs for each of the models to those inputs that are required solely for each particular pollutant.

The challenge with building separate models is how to combine the predicted probabilities of the individual models to arrive at the predicted overall probability. We meet the challenge by using theory to combine the predicted probabilities of the individual models. Below, we demonstrate the theory by pretending that the overall ASM test is made up of a separate test for HC, CO, and NX. The extension to the actual case of six tests follows by analogy.

When the predicted probabilities of an event occurring are independent of each other, then the probability of a series of events occurring is simple. For example, the probability of having three daughters is simply the product of the probabilities of having a single daughter. That is, 0.5 * 0.5 * 0.5 = 0.125. This combination of probabilities is applicable when the probability of a subsequent event is independent of what happened on the previous event. In other words, the probability of the second birth being a daughter is 0.5, and this value is independent of whether the first child was a son or a daughter.

In the case of ASM pass/fail results for HC, CO, and NX, the probabilities of passing and failing are not independent of each other. For example, we know from past observations that vehicles that have high HC also tend to have high CO. Also, vehicles that tend to have very high CO tend to have lower NX emissions. Accordingly, we need to find a theoretical relationship that takes the dependences of the probabilities of passing and failing ASM HC, CO, and NX tests into account.

Fortunately, the solution to this problem has been worked out many years ago and is explained near the beginning of most statistical textbooks covering probability. The overall probability that a vehicle will fail one or more of an I/M HC, CO, and NX tests is given by:

$$P_{Overall,Fail} = 1 - [(NX_{pass}) \bullet (HC_{pass} | NX_{pass}) \bullet (CO_{pass} | HC_{pass}, NX_{pass})]$$

where:

NX_{pass}	=	the probability that ASM NX will pass
HC_{pass} * NX_{pass}	=	the probability that HC will pass given that NX already passed
CO_{pass} * HC_{pass}, NX_{pass}	=	the probability that CO will pass given that HC and NX already passed

This relationship is developed in probability text books and can be verified using a Venn diagram. We demonstrate it here by considering all possible ASM results as shown in Table I-1. Note that the order of the pollutants in the above equation is not important.

Table I-1 shows all eight possible combinations of NX, HC, and CO pass/fail results and the overall result of the tests. Passes are designated as 1 and fails are designated as 0. The fifth column shows the result of Model A which predicts the probability that NX will be a pass. If it is a good model, it will have the same values as Column 1. In the next column, Model B shows the results for the probability of HC passing given that NX already passed. NX passes only for the last four lines in the table. Therefore, a good model for Model B will have the same values for the last four lines as for the last four lines of the second column for HC. Similarly, Model C predicts the probability of CO passing given that HC and NX already passed. The only combination of results for which HC and NX did not already pass is the last two lines in the table. Therefore, Model C will be a good model if it has the same values in the last two lines as the values for the third column of the table. The overall probability of failing, then, is given in the last column of the table according to the equation above. The values for Model B and Model C in the table designated as "Not Relevant" will not influence the result of the overall failure probability because at least one factor in the ABC term will be zero. The overall probability of failure as shown in the last column for the eight combinations is in agreement with the ASM overall results shown in the fourth column.

The above relation indicates that two of the three passing models for the individual pollutants are not simply models that give the passing or failing probability of the individual pollutants. They are models that give the passing probability of the pollutant being modeled given that one or two of the other pollutants has already passed. This is the key element of combining the probabilities of events that are dependent on each other. During model building, these models are trained on a subset of the complete dataset. Specifically, Model A for the probability of NX passing is trained on the entire dataset. Model B for HC passing given that

NX already passed is trained on a subset of the entire dataset. First, all those observations in the entire dataset where NX failed are removed from the dataset and then Model B is trained on the remaining observations. Similarly, Model C for the probability of CO passing given that HC and NX already passed is trained on a subset of the full dataset for which all observations where HC failed or NX failed are removed from the dataset. The model is then trained on the remaining observations for CO passing and failing.

Table I-1. Demonstration of Theory

ASM Results (1 = Pass, 0 = Fail)				Model A P_{pass}	Model B P_{pass}	Model C P_{pass}	Overall P_{fail}
NX	**HC**	**CO**	**OA**	**P (NX)**	**P (HC*NX)**	**P (CO*HC, NX)**	**1 – A C B C C**
0	0	0	0	0	Not Relevant	Not Relevant	1
0	0	1	0	0	Not Relevant	Not Relevant	1
0	1	0	0	0	Not Relevant	Not Relevant	1
0	1	1	0	0	Not Relevant	Not Relevant	1
1	0	0	0	1	0	Not Relevant	1
1	0	1	0	1	0	Not Relevant	1
1	1	0	0	1	1	0	1
1	1	1	1	1	1	1	0

Appendix J

Vehicle Descriptions and Model Years for Abundant Data

Metering_ECS	Make_CarTrk	Engine	MY74	MY75	MY76	MY77	MY78	MY79	MY80	MY81	MY82	MY83	MY84	MY85	MY86	MY87	MY88	MY89	MY90	MY91	MY92	MY93	MY94	MY95	MY96	MY97	MY98	MY99	MY00	MY01	MY02
CAOE	AMERICAN_CAR	232CI_L6_N		49	65	53		24																							
CAOE	AMERICAN_CAR	258CI_L6_N		99	224	229	327	294																							
CAOE	AMERICAN_CAR	304CI_V8_N		23	13		10	10																							
CAOE	BUICK_CAR	3.8L_V6_T							51																						
CAOE	BUICK_CAR	4.9L_V8_N							144																						
CAOE	BUICK_CAR	5.0L_V8_N							548																						
CAOE	BUICK_CAR	5.7L_V8_N							1,065																						
CAOE	CADILLAC_CAR	6.0L_V8_N							3,036																						
CAOE	CHEVROLET_CAR	1.6L_L4_N						621	771																						
CAOE	CHEVROLET_CAR	250CI_L6_N		1,151	1,693																										
CAOE	CHEVROLET_CAR	4.4L_V8_N							430																						
CAOE	CHEVROLET_CAR	400CI_V8_N			628																										
CAOE	CHEVROLET_CAR	5.0L_V8_N							4,739																						
CAOE	CHEVROLET_CAR	5.7L_V8_N							817																						
CAOE	CHEVROLET_CAR	98CI_L4_N			112	124																									
CAOE	CHEVROLET_TRK	1.8L_L4_N						2,082	2,016	276																					
CAOE	CHEVROLET_TRK	4.1L_L6_N						2,779	2,679	2,622																					
CAOE	CHEVROLET_TRK	5.0L_V8_N								5,478																					
CAOE	CHEVROLET_TRK	5.7L_V8_N						18,216	9,455	6,409																					
CAOE	CHRYSLER_CAR	2.6L_L4_N									914																				
CAOE	CHRYSLER_CAR	3.7L_L6_N						102	179																						
CAOE	CHRYSLER_CAR	318CI_V8_N				225	437																								
CAOE	CHRYSLER_CAR	360CI_V8_N		231	459	962	937	1,181																							
CAOE	CHRYSLER_CAR	400CI_V8_N		43	105	67	57																								
CAOE	CHRYSLER_CAR	440CI_V8_N		63	80	165																									
CAOE	CHRYSLER_CAR	5.2L_V8_N						702	561																						
CAOE	DATSUN_CAR	1.5L_L4_N								3,366	5,376																				
CAOE	DATSUN_CAR	1.9L_L4_N									1,173	1,471																			
CAOE	DATSUN_CAR	2.0L_L4_N								1,366																					
CAOE	DATSUN_TRK	2.2L_L4_N								3,663	5,562																				
CAOE	DODGE/MITS_TRK	2.0L_L4_N								409	422	480																			
CAOE	DODGE_CAR	1.6L_L4_N			80	137	244	224	268																						
CAOE	DODGE_CAR	1.7L_L4_N					57	77	79																						
CAOE	DODGE_CAR	2.6L_L4_N								294	455																				
CAOE	DODGE_CAR	225CI_L6_N		419	406	399	241																								
CAOE	DODGE_CAR	3.7L_L6_N						196	263																						
CAOE	DODGE_CAR	318CI_V8_N		313	403	731	527																								
CAOE	DODGE_CAR	360CI_V8_N		63	73	162	262	282	88																						
CAOE	DODGE_CAR	5.2L_V8_N						530	263																						
CAOE	DODGE_TRK	2.2L_L4_N									230	215																			
CAOE	DODGE_TRK	2.5L_L4_N											2,295	4,439																	
CAOE	DODGE_TRK	3.7L_V6_N								1,361	2,181	1,759	1,261	1,274																	
CAOE	DODGE_TRK	5.2L_V8_N								1,743	3,903	6,010	8,280	9,440	6,991	8,430															
CAOE	DODGE_TRK	5.9L_V8_N										701	1,447	2,389	3,148	2,872	888														
CAOE	FORD_CAR	1.6L_L4_N								619	1,254	1,032	1,902	1,812																	
CAOE	FORD_CAR	1.9L_L4_N												2,081	6,430																
CAOE	FORD_CAR	139CI_L4_N			501	472	616																								
CAOE	FORD_CAR	169CI_V6_N			490	250	569																								
CAOE	FORD_CAR	2.3L_L4_N						1,734	1,583																						
CAOE	FORD_CAR	2.8L_V6_N						786																							
CAOE	FORD_CAR	200CI_L6_N					1,588																								
CAOE	FORD_CAR	250CI_L6_N		613	1,068	695	530		64																						
CAOE	FORD_CAR	3.3L_L6_N						1,529		4,526	3,591	2,329																			
CAOE	FORD_CAR	3.8L_V6_N										6,749																			
CAOE	FORD_CAR	302CI_V8_N		571	1,179	1,684	2,102																								
CAOE	FORD_CAR	351CI_V8_N		638	1,101	1,969	2,144																								
CAOE	FORD_CAR	4.1L_L6_N						892																							
CAOE	FORD_CAR	4.2L_V8_N							698																						
CAOE	FORD_CAR	400CI_V8_N		385	637	2,183	2,062																								
CAOE	FORD_CAR	460CI_V8_N		160	287	36																									
CAOE	FORD_CAR	5.0L_V8_N						2,621																							
CAOE	FORD_CAR	5.8L_V8_N						4,251																							
CAOE	FORD_TRK	2.0L_L4_N					1,719					136	213	181	197	168	280														
CAOE	FORD_TRK	2.3L_L4_T					11,734																								

Metering_ECS	Make_CarTrk	Engine	MY74	MY75	MY76	MY77	MY78	MY79	MY80	MY81	MY82	MY83	MY84	MY85	MY86	MY87	MY88	MY89	MY90	MY91	MY92	MY93	MY94	MY95	MY96	MY97	MY98	MY99	MY00	MY01	MY02
CAOE	FORD_TRK	4.9L_I6_N					13,063																								
CAOE	FORD_TRK	5.0L_V8_N					2,932																								
CAOE	FORD_TRK	5.8L_V8_N					49,424			4,322			1,742	3,089	2,638	1,979															
CAOE	FORD_TRK	6.1L_V8_N								367	301	267																			
CAOE	FORD_TRK	6.6L_V8_N								2,294	3,644																				
CAOE	GMC_TRK	4.1L_L6_N						732	582	613																					
CAOE	GMC_TRK	5.0L_V8_N								1,026																					
CAOE	GMC_TRK	5.7L_V8_N						4,891	2,315	1,816																					
CAOE	HONDA_CAR	1.3L_L4_N									716	1,142																			
CAOE	HONDA_CAR	1.5L_L4_N									4,625	6,172																			
CAOE	HONDA_CAR	1.8L_L4_N									13,056	19,152																			
CAOE	JEEP_TRK	258CI_L6_N			628	603	551	1,014	855																						
CAOE	JEEP_TRK	304CI_V8_N		217	378	656	971	1,033	359																						
CAOE	JEEP_TRK	360CI_V8_N				446	735	1,067	468	153	221	439	928	716	822	1,014	883														
CAOE	JEEP_TRK	5.9L_V8_N																902	564	247											
CAOE	LINCOLN_CAR	302CI_V8_N				259	91																								
CAOE	LINCOLN_CAR	400CI_V8_N				1,502	1,777																								
CAOE	LINCOLN_CAR	460CI_V8_N		518	986	340	382																								
CAOE	MAZDA_CAR	1.5L_L4_N								549	653																				
CAOE	MAZDA_CAR	2.0L_L4_N								436	849																				
CAOE	MERCEDES_CAR	2.3L_L4_N	109	140	33	65																									
CAOE	MERCEDES_CAR	2.8L_L6_N	322	538	591	133																									
CAOE	MERCURY_CAR	1.6L_L4_N								200	303	211	262	452																	
CAOE	MERCURY_CAR	1.9L_L4_N												378	863																
CAOE	MERCURY_CAR	2.3L_L4_N						325	274																						
CAOE	MERCURY_CAR	2.8L_V6_N						197																							
CAOE	MERCURY_CAR	200CI_L6_N					461																								
CAOE	MERCURY_CAR	250CI_L6_N		136	205	129	165		26																						
CAOE	MERCURY_CAR	3.3L_L6_N								1,437	1,000	708																			
CAOE	MERCURY_CAR	3.8L_V6_N										2,037																			
CAOE	MERCURY_CAR	302CI_V8_N		146	302	421																									
CAOE	MERCURY_CAR	351CI_V8_N		177	343	469	662																								
CAOE	MERCURY_CAR	4.1L_L6_N						271																							
CAOE	MERCURY_CAR	4.2L_V8_N							177																						
CAOE	MERCURY_CAR	400CI_V8_N		52	123	481	530																								
CAOE	MERCURY_CAR	460CI_V8_N		89	139	48	57																								
CAOE	MERCURY_CAR	5.0L_V8_N						891																							
CAOE	MERCURY_CAR	5.8L_V8_N						1,046																							
CAOE	OLDSMOBILE_CAR	250CI_L6_N		51	89																										
CAOE	OLDSMOBILE_CAR	4.3L_V8_N							967																						
CAOE	OLDSMOBILE_CAR	5.0L_V8_N							1,184																						
CAOE	OLDSMOBILE_CAR	5.7L_V8_N							811																						
CAOE	PLYMOUTH_CAR	1.6L_L4_N			51	43	79	64	309																						
CAOE	PLYMOUTH_CAR	1.7L_L4_N					75	100	98																						
CAOE	PLYMOUTH_CAR	2.0L_L4_N			36	35	55																								
CAOE	PLYMOUTH_CAR	2.6L_L4_N								511	228																				
CAOE	PLYMOUTH_CAR	225CI_L6_N		448	435	449	331																								
CAOE	PLYMOUTH_CAR	3.7L_L6_N						290	224																						
CAOE	PLYMOUTH_CAR	318CI_V8_N		218	460	574	324																								
CAOE	PLYMOUTH_CAR	360CI_V8_N		45	50	112	45	59	90																						
CAOE	PLYMOUTH_CAR	5.2L_V8_N						307	93																						
CAOE	PLYMOUTH_TRK	2.5L_L4_N											1,619	3,511																	
CAOE	PLYMOUTH_TRK	5.2L_V8_N								40	62	76																			
CAOE	PONTIAC_CAR	151CI_L4_N				51																									
CAOE	PONTIAC_CAR	250CI_L6_N		80	156																										
CAOE	PONTIAC_CAR	4.9L_V8_N							234																						
CAOE	PONTIAC_CAR	4.9L_V8_T							68																						
CAOE	PONTIAC_CAR	400CI_V8_N			730																										
CAOE	PONTIAC_CAR	5.0L_V8_N							674																						
CAOE	PONTIAC_CAR	5.7L_V8_N							112																						
CAOE	ROLLSROYCE_CAR	6.8L_V8_N				192	246	409	75																						
CAOE	TOYOTA_CAR	1.3L_L4_N								880	860																				
CAOE	TOYOTA_CAR	1.6L_L4_N				2,021	2,964	3,554																							
CAOE	TOYOTA_CAR	1.8L_L4_N							9,520																						

Metering_ECS	Make_CarTrk	Engine	MY74	MY75	MY76	MY77	MY78	MY79	MY80	MY81	MY82	MY83	MY84	MY85	MY86	MY87	MY88	MY89	MY90	MY91	MY92	MY93	MY94	MY95	MY96	MY97	MY98	MY99	MY00	MY01	MY02
CAOE	TOYOTA_CAR	2.2L_L4_N		420	3,263	7,343	10,146	11,664	16,896																						
CAOE	TOYOTA_CAR	2.6L_L6_N			37		496	621																							
CAOE	TOYOTA_CAR	4.2L_L6_N						199	106																						
CAOE	TOYOTA_TRK	2.3L_L4_N								10,414	13,938	14,980	28,084	41,603																	
CAOE	TOYOTA_TRK	2.4L_L4_N																	22,292												
CAOE	TOYOTA_TRK	4.2L_L6_N								130	429	434	728	902	453																
CATE	AMERICAN_CAR	151CI_L4_N								51	15																				
CATE	AMERICAN_CAR	258CI_L6_N							364	277	334	258																			
CATE	AMERICAN_TRK	258CI_L6_N								149	224	237	305	252	95	86															
CATE	BUICK_CAR	2.5L_L4_N								909																					
CATE	BUICK_CAR	2.8L_V6_N							529	772	806	1,168	1,937																		
CATE	BUICK_CAR	3.0L_V6_N									800	1,498	5,298																		
CATE	BUICK_CAR	3.8L_V6_N							3,290	6,021	3,712	3,044	5,317		797																
CATE	BUICK_CAR	3.8L_V6_T								62		207																			
CATE	BUICK_CAR	4.1L_L6_N								304																					
CATE	BUICK_CAR	4.1L_V6_N									1,515	2,631	1,062																		
CATE	BUICK_CAR	4.3L_V8_N								360																					
CATE	BUICK_CAR	5.0L_V8_N								830	1,600	3,175	4,186	3,985	2,103	1,005	258	182	227												
CATE	CADILLAC_CAR	1.8L_L4_N									641																				
CATE	CADILLAC_CAR	4.1L_L6_N								716																					
CATE	CADILLAC_CAR	4.1L_V6_N									467																				
CATE	CADILLAC_CAR	5.0L_V8_N													1,916	2,785	1,734	1,595	166												
CATE	CHEV/SUZUKI_CAR	1.0L_L3_N												2,406	2,769	2,721	2,368														
CATE	CHEVROLET_CAR	1.5L_L4_N													2,869	2,397		3,039													
CATE	CHEVROLET_CAR	1.6L_L4_N								818	531	452	950	859	7,985	6,258	5,572														
CATE	CHEVROLET_CAR	1.8L_L4_N									988																				
CATE	CHEVROLET_CAR	2.5L_L4_N								935																					
CATE	CHEVROLET_CAR	2.8L_V6_N							828	738	3,286	3,324	9,267																		
CATE	CHEVROLET_CAR	3.8L_V6_N							4,206	5,102	2,394	2,325	1,233																		
CATE	CHEVROLET_CAR	4.4L_V8_N								367	234																				
CATE	CHEVROLET_CAR	5.0L_V8_N								1,766	4,906	6,889	13,128	8,866	8,638	6,179	3,040	395													
CATE	CHEVROLET_CAR	5.7L_V8_N								2,453	89		97		530	774	715														
CATE	CHEVROLET_TRK	1.9L_L4_N									857	334	491	68																	
CATE	CHEVROLET_TRK	2.8L_V6_N									6,429	10,858	18,319	21,891																	
CATE	CHEVROLET_TRK	3.8L_V6_N								1,972	1,191	795	632																		
CATE	CHEVROLET_TRK	4.1L_L6_N									1,380	909	1,255																		
CATE	CHEVROLET_TRK	4.3L_V6_N												6,762	1,175																
CATE	CHEVROLET_TRK	5.0L_V8_N									6,733	8,306	13,631	14,217	12,500																
CATE	CHEVROLET_TRK	5.7L_V8_N									5,033	5,131	11,701	13,261	11,048	1,117	471														
CATE	CHEVROLET_TRK	7.4L_V8_N									2,783	4,390	7,847	8,319	7,953	4,658	4,008	4,552													
CATE	CHRYSLER_CAR	2.2L_L4_N									323		144																		
CATE	CHRYSLER_CAR	2.6L_L4_N											3,024	1,207																	
CATE	CHRYSLER_CAR	3.7L_L6_N								162		1,872																			
CATE	CHRYSLER_CAR	5.2L_V8_N								303	1,197	2,473	2,736	4,906	3,737	5,071	2,230	976													
CATE	DATSUN_CAR	1.6L_L4_N										9,051																			
CATE	DODGE/MITS_CAR	1.4L_L4_N								84	136	170																			
CATE	DODGE/MITS_CAR	1.5L_L4_N												977	2,192	1,983	2,021														
CATE	DODGE/MITS_CAR	1.6L_L4_N								216	187	194	300																		
CATE	DODGE/MITS_CAR	1.9L_L4_N											248																		
CATE	DODGE/MITS_TRK	2.0L_L4_N											1,261	2,515	3,659	2,837	2,600	1,698													
CATE	DODGE_CAR	2.2L_L4_N								347	508		2,171	1,823	547	1,439															
CATE	DODGE_CAR	2.2L_L4_T										1,172																			
CATE	DODGE_CAR	2.6L_L4_N											838	767																	
CATE	DODGE_CAR	3.7L_L6_N								75	48	749																			
CATE	DODGE_CAR	5.2L_V8_N								152	134	273	256	708	245	790	658	181													
CATE	DODGE_TRK	2.2L_L4_N											733	820	454	1,000	596														
CATE	DODGE_TRK	2.5L_L4_N													4,817	2,760		949													
CATE	DODGE_TRK	3.7L_V6_N													828	1,107															
CATE	DODGE_TRK	3.9L_V6_N														4,255															
CATE	FORD_CAR	1.3L_L4_N															5,775	1,887													
CATE	FORD_CAR	2.3L_L4_N								1,021	736	505	6,256	2,345	2,743																
CATE	FORD_CAR	3.8L_V6_N									963																				
CATE	FORD_CAR	4.2L_V8_N								758	485																				
CATE	FORD_CAR	5.0L_V8_N								745	2,548	6,141	8,097	10,714	7,448																

Metering_ECS	Make_CarTrk	Engine	MY74	MY75	MY76	MY77	MY78	MY79	MY80	MY81	MY82	MY83	MY84	MY85	MY86	MY87	MY88	MY89	MY90	MY91	MY92	MY93	MY94	MY95	MY96	MY97	MY98	MY99	MY00	MY01	MY02
CATE	FORD_CAR	5.8L_V8_N								357			150	250	66	100	106	99	532	2,136											
CATE	FORD_TRK	2.3L_L4_N										4,640	3,132																		
CATE	FORD_TRK	2.8L_V6_N										2,300	10,928	12,183	3,657																
CATE	FORD_TRK	4.9L_I6_N								6,752	5,211	4,218	6,071	6,641	7,281																
CATE	FORD_TRK	5.0L_V8_N								3,261	3,365	5,783	8,766	4,998																	
CATE	FORD_TRK	5.8L_V8_N									3,992	2,828	3,305	3,334																	
CATE	GMC_TRK	1.9L_L4_N									244	70	122																		
CATE	GMC_TRK	2.8L_V6_N									1,531	2,274	4,444	4,901																	
CATE	GMC_TRK	3.8L_V6_N								244	155	98	92																		
CATE	GMC_TRK	4.1L_L6_N									213	176	192																		
CATE	GMC_TRK	4.3L_V6_N												1,257	409																
CATE	GMC_TRK	5.0L_V8_N									1,268	1,691	2,939	3,029	2,646																
CATE	GMC_TRK	5.7L_V8_N									1,402	1,260	3,052	3,749	3,376	219															
CATE	GMC_TRK	7.4L_V8_N									536	708	1,238	2,098	1,829	379	369	228													
CATE	HONDA_CAR	1.5L_L4_N											10,242	12,499	15,613	23,187															
CATE	HONDA_CAR	1.8L_L4_N											30,312	33,771	3,504	2,559															
CATE	HONDA_CAR	2.0L_L4_N														29,420	35,532	30,460													
CATE	HYUNDAI_CAR	1.5L_L4_N													4,374	10,990	19,685														
CATE	ISUZU_TRK	2.3L_L4_N																	850	807	621	472									
CATE	JEEP_TRK	150CI_L4_N											1,744	2,850	231																
CATE	JEEP_TRK	173CI_V6_N											1,647	3,852	7,601																
CATE	JEEP_TRK	258CI_L6_N								1,348	1,622	2,402	2,579	2,784	1,930	3,215	3,073														
CATE	JEEP_TRK	3.9L_V6_N																682													
CATE	JEEP_TRK	4.2L_L6_N																	3,331												
CATE	JEEP_TRK	4.2L_V6_N																2,882													
CATE	LINCOLN_CAR	5.0L_V8_N									1,930																				
CATE	MAZDA_CAR	1.5L_L4_N										767																			
CATE	MAZDA_CAR	2.0L_L4_N										1,905	4,171	6,907																	
CATE	MAZDA_TRK	2.0L_L4_N													16,860																
CATE	MAZDA_TRK	2.2L_L4_N														17,608															
CATE	MAZDA_TRK	2.6L_L4_N														1,240															
CATE	MERCURY_CAR	2.3L_L4_N								201	107	98	1,973	151	105																
CATE	MERCURY_CAR	3.8L_V6_N									383																				
CATE	MERCURY_CAR	4.2L_V8_N								271	110																				
CATE	MERCURY_CAR	5.0L_V8_N								276	941	2,522	4,237	5,604	4,058																
CATE	MERCURY_CAR	5.8L_V8_N								218																					
CATE	MITSUBISHI_CAR	1.5L_L4_N												498	1,086	1,811	1,919	2,800													
CATE	MITSUBISHI_CAR	2.0L_L4_N											672	939	830	887	533														
CATE	MITSUBISHI_TRK	2.0L_L4_N											584	2,002	3,119	5,668	7,185	3,162													
CATE	MITSUBISHI_TRK	2.6L_L4_N											235	323	329	2,831	809	216													
CATE	NISSAN_CAR	1.6L_L4_N												16,777	13,169																
CATE	NISSAN_TRK	2.4L_L4_N												19,321																	
CATE	OLDSMOBILE_CAR	2.5L_L4_N								576																					
CATE	OLDSMOBILE_CAR	2.8L_V6_N							168	253	210	337	500																		
CATE	OLDSMOBILE_CAR	3.0L_V6_N									468	1,418	3,654																		
CATE	OLDSMOBILE_CAR	3.8L_V6_N							2,551	5,653	5,781	7,535	9,451		1,913																
CATE	OLDSMOBILE_CAR	4.3L_V8_N								956	622																				
CATE	OLDSMOBILE_CAR	5.0L_V8_N								1,253	2,364	5,825	8,055	7,850	5,063	2,782	817	220													
CATE	PLYM/MITS_CAR	1.4L_L4_N								58	119	137	267																		
CATE	PLYM/MITS_CAR	1.5L_L4_N												812	1,826	1,616	1,398														
CATE	PLYM/MITS_CAR	1.6L_L4_N								218	129	148	209																		
CATE	PLYM/MITS_CAR	2.6L_L4_N										223																			
CATE	PLYMOUTH_CAR	2.2L_L4_N								427	534	1,258	2,302	1,931	663	1,416															
CATE	PLYMOUTH_CAR	2.6L_L4_N										265	272	614																	
CATE	PLYMOUTH_CAR	5.2L_V8_N									32		96	185	113	255	186	37													
CATE	PLYMOUTH_TRK	2.2L_L4_N											223	390	268	280															
CATE	PLYMOUTH_TRK	2.5L_L4_N													3,996	2,158															
CATE	PONTIAC_CAR	1.6L_L4_N									112	81	154	172	101	56															
CATE	PONTIAC_CAR	1.8L_L4_N									367																				
CATE	PONTIAC_CAR	2.5L_L4_N								238																					
CATE	PONTIAC_CAR	2.8L_V6_N							162	84	702	1,041	2,782																		
CATE	PONTIAC_CAR	3.8L_V6_N							846	1,170	462	591	771		331																
CATE	PONTIAC_CAR	4.1L_V6_N									352																				
CATE	PONTIAC_CAR	4.3L_V8_N								297																					

Metering_ECS	Make_CarTrk	Engine	MY74	MY75	MY76	MY77	MY78	MY79	MY80	MY81	MY82	MY83	MY84	MY85	MY86	MY87	MY88	MY89	MY90	MY91	MY92	MY93	MY94	MY95	MY96	MY97	MY98	MY99	MY00	MY01	MY02
CATE	PONTIAC_CAR	4.9L_V8_N								208																					
CATE	PONTIAC_CAR	4.9L_V8_T								283																					
CATE	PONTIAC_CAR	5.0L_V8_N								249	1,344	1,720	4,849	3,206	2,730	1,129															
CATE	SUBARU_CAR	1.2L_L3_N															1,094	970													
CATE	SUBARU_CAR	1.6L_H4_N								97	119	118	212	181	303	215															
CATE	SUBARU_CAR	1.8L_H4_N								1,052	1,969	1,827	2,970	4,104	5,773	5,698															
CATE	TOYOTA_CAR	1.5L_L4_N								2,972	5,329	9,046	8,199	7,627	6,695	11,269	13,705	18,793	5,933												
CATE	TOYOTA_CAR	1.6L_L4_N										11,058	15,148	14,502	17,936	19,470	29,015	30,886													
CATE	TOYOTA_CAR	1.8L_L4_N								11,012	11,562																				
CATE	TOYOTA_CAR	2.4L_L4_N								6,923	10,166	1,922																			
CNOE	BUICK_CAR	231CI_V6_N		114	646	627	2,024																								
CNOE	BUICK_CAR	260CI_V8_N		69	98																										
CNOE	BUICK_CAR	3.8L_V6_N						2,057																							
CNOE	BUICK_CAR	3.8L_V6_T					212	398																							
CNOE	BUICK_CAR	301CI_V8_N				66	77																								
CNOE	BUICK_CAR	305CI_V8_N					1,293																								
CNOE	BUICK_CAR	350CI_V8_N		423	770	1,760	966																								
CNOE	BUICK_CAR	4.9L_V8_N						305																							
CNOE	BUICK_CAR	403CI_V8_N				1,099	1,002																								
CNOE	BUICK_CAR	455CI_V8_N		243	351																										
CNOE	BUICK_CAR	5.0L_V8_N						1,444																							
CNOE	BUICK_CAR	5.7L_V8_N						1,614																							
CNOE	BUICK_CAR	6.6L_V8_N						727																							
CNOE	CADILLAC_CAR	425CI_V8_N				4,929	6,296																								
CNOE	CADILLAC_CAR	500CI_V8_N		1,704	2,560																										
CNOE	CADILLAC_CAR	7.0L_V8_N						6,613																							
CNOE	CHEVROLET_CAR	1.6L_L4_N					379																								
CNOE	CHEVROLET_CAR	231CI_V6_N					1,687																								
CNOE	CHEVROLET_CAR	250CI_L6_N				2,027	1,760																								
CNOE	CHEVROLET_CAR	3.3L_V6_N					156	231																							
CNOE	CHEVROLET_CAR	3.8L_V6_N						2,254																							
CNOE	CHEVROLET_CAR	305CI_V8_N			1,834	6,931	9,711																								
CNOE	CHEVROLET_CAR	350CI_V8_N		4,863	5,804	9,068	7,549																								
CNOE	CHEVROLET_CAR	4.1L_L6_N						1,085																							
CNOE	CHEVROLET_CAR	4.4L_V8_N						519																							
CNOE	CHEVROLET_CAR	400CI_V8_N		648																											
CNOE	CHEVROLET_CAR	5.0L_V8_N						10,601																							
CNOE	CHEVROLET_CAR	5.7L_V8_N						7,100																							
CNOE	CHEVROLET_TRK	110CI_L4_N		904	571		1,411																								
CNOE	CHEVROLET_TRK	250CI_L6_N		844	803	1,354	1,805																								
CNOE	CHEVROLET_TRK	305CI_V8_N				346	442																								
CNOE	CHEVROLET_TRK	5.0L_V8_N						545	263	274																					
CNOE	DATSUN_CAR	1.2L_L4_N							235																						
CNOE	DATSUN_CAR	1.4L_L4_N							1,547																						
CNOE	DATSUN_CAR	1.9L_L4_N							2,750																						
CNOE	DODGE_TRK	225CI_V6_N				432	618	110	814																						
CNOE	DODGE_TRK	318CI_V8_N				4,425	2,171	3,918	1,109																						
CNOE	DODGE_TRK	360CI_V8_N					6,527	8,503	1,706																						
CNOE	FORD_CAR	3.3L_L6_N							3,609																						
CNOE	GMC_CAR	231CI_V6_N					51																								
CNOE	GMC_CAR	305CI_V8_N					56																								
CNOE	GMC_CAR	350CI_V8_N			88	281	310																								
CNOE	GMC_TRK	250CI_L6_N		154	214	379	493																								
CNOE	GMC_TRK	305CI_V8_N				54	76																								
CNOE	GMC_TRK	5.0L_V8_N						95	38	49																					
CNOE	HONDA_CAR	1.3L_L4_N							88	717			2,151			2,029															
CNOE	HONDA_CAR	1.5L_L4_N			524	639	810	1,139	3,245	4,629						1,375															
CNOE	HONDA_CAR	1.6L_L4_N			89	500	722																								
CNOE	HONDA_CAR	1.8L_L4_N						2,373	4,958	7,617																					
CNOE	JEEP_TRK	151CI_L4_N							504	525	196	50																			
CNOE	MERCURY_CAR	3.3L_L6_N							779																						
CNOE	OLDSMOBILE_CAR	231CI_V6_N				280	405																								
CNOE	OLDSMOBILE_CAR	260CI_V8_N		107	205		4,137																								
CNOE	OLDSMOBILE_CAR	3.8L_V6_N						808																							

Metering_ECS	Make_CarTrk	Engine	MY74	MY75	MY76	MY77	MY78	MY79	MY80	MY81	MY82	MY83	MY84	MY85	MY86	MY87	MY88	MY89	MY90	MY91	MY92	MY93	MY94	MY95	MY96	MY97	MY98	MY99	MY00	MY01	MY02
CNOE	OLDSMOBILE_CAR	305CI_V8_N					1,188																								
CNOE	OLDSMOBILE_CAR	350CI_V8_N		737	1,769	3,587	1,466																								
CNOE	OLDSMOBILE_CAR	4.3L_V8_N						4,605																							
CNOE	OLDSMOBILE_CAR	403CI_V8_N				982	792																								
CNOE	OLDSMOBILE_CAR	455CI_V8_N		226	350																										
CNOE	OLDSMOBILE_CAR	5.0L_V8_N						1,904																							
CNOE	OLDSMOBILE_CAR	5.7L_V8_N						1,671																							
CNOE	OLDSMOBILE_CAR	6.6L_V8_N						519																							
CNOE	PLYMOUTH_TRK	318CI_V8_N				65	40	71	38																						
CNOE	PLYMOUTH_TRK	360CI_V8_N					180	241	104																						
CNOE	PONTIAC_CAR	231CI_V6_N			44	198	317																								
CNOE	PONTIAC_CAR	260CI_V8_N		39	105																										
CNOE	PONTIAC_CAR	3.8L_V6_N						570																							
CNOE	PONTIAC_CAR	301CI_V8_N				205	356																								
CNOE	PONTIAC_CAR	305CI_V8_N				39	1,332																								
CNOE	PONTIAC_CAR	350CI_V8_N		313	536	1,022	648																								
CNOE	PONTIAC_CAR	4.9L_V8_N						668																							
CNOE	PONTIAC_CAR	400CI_V8_N		317		295	329																								
CNOE	PONTIAC_CAR	403CI_V8_N				1,292	1,576																								
CNOE	PONTIAC_CAR	455CI_V8_N		88	113																										
CNOE	PONTIAC_CAR	5.0L_V8_N						1,376																							
CNOE	PONTIAC_CAR	5.7L_V8_N						630																							
CNOE	PONTIAC_CAR	6.6L_V8_N						2,222																							
CNOE	TOYOTA_CAR	1.2L_L4_N				32	100	22																							
CNOE	TOYOTA_CAR	1.5L_L4_N							1,830																						
CNTE	BUICK_CAR	2.5L_L4_N							423																						
CNTE	BUICK_CAR	2.8L_V6_N												161	426																
CNTE	BUICK_CAR	3.0L_V6_N												3,159																	
CNTE	BUICK_CAR	3.8L_V6_N												3,982		675															
CNTE	CHEVROLET_CAR	1.5L_L4_N												96																	
CNTE	CHEVROLET_CAR	2.5L_L4_N							892																						
CNTE	CHEVROLET_CAR	2.8L_V6_N												887	656																
CNTE	CHRYSLER_CAR	2.2L_L4_T											1,444	5,459	6,058	6,936	4,170	178													
CNTE	CHRYSLER_CAR	2.5L_L4_N													1,939	2,326	2,110	2,024													
CNTE	CHRYSLER_CAR	2.5L_L4_T																3,520													
CNTE	DATSUN_TRK	2.4L_L4_N										4,877																			
CNTE	DODGE_CAR	2.2L_L4_T											676		1,872	1,729	941	159													
CNTE	DODGE_CAR	2.5L_L4_N													2,093	2,404	4,049	4,904													
CNTE	DODGE_CAR	2.5L_L4_T																1,187													
CNTE	HONDA_CAR	1.3L_L4_N												1,005	1,905																
CNTE	HONDA_CAR	1.5L_L4_N												1,830	1,688																
CNTE	HONDA_CAR	2.0L_L4_N													25,143	392	4,838	312													
CNTE	HYUNDAI_CAR	1.5L_L4_N																10,443													
CNTE	MAZDA_TRK	2.2L_L4_N																10,887													
CNTE	MAZDA_TRK	2.6L_L4_N															124	570													
CNTE	MITSUBISHI_CAR	1.5L_L4_N																1,152													
CNTE	NISSAN_CAR	1.6L_L4_N											11,606																		
CNTE	NISSAN_TRK	2.4L_L4_N											15,403																		
CNTE	OLDSMOBILE_CAR	2.5L_L4_N							212																						
CNTE	OLDSMOBILE_CAR	2.8L_V6_N													606																
CNTE	OLDSMOBILE_CAR	3.0L_V6_N												3,464																	
CNTE	OLDSMOBILE_CAR	3.8L_V6_N												5,791		1,101															
CNTE	PLYMOUTH_CAR	2.2L_L4_T												259	298	970	359														
CNTE	PLYMOUTH_CAR	2.5L_L4_N													1,407	1,655	2,673	3,852													
CNTE	PLYMOUTH_CAR	2.5L_L4_T																832													
CNTE	PONTIAC_CAR	2.5L_L4_N							498																						
CNTE	PONTIAC_CAR	2.8L_V6_N												308	166																
CNTE	PONTIAC_CAR	3.8L_V6_N												639																	
CNTE	SUBARU_CAR	1.8L_H4_N															2,099	1,133													
CNTE	SUZUKI_TRK	1.3L_L4_N													4,857	6,975	4,920	229													
CNTE	TOYOTA_CAR	2.4L_L4_N												2,647																	
FATE	ACURA_CAR	2.5L_V6_N													3,492	7,164															
FATE	ACURA_CAR	2.7L_V6_N														2,639	16,815	14,242	14,398												
FATE	ACURA_CAR	3.0L_V6_N																		71	360	193	172	210							

Metering_ECS	Make_CarTrk	Engine	MY74	MY75	MY76	MY77	MY78	MY79	MY80	MY81	MY82	MY83	MY84	MY85	MY86	MY87	MY88	MY89	MY90	MY91	MY92	MY93	MY94	MY95	MY96	MY97	MY98	MY99	MY00	MY01	MY02
FATE	ACURA_CAR	3.2L_V6_N																		15,030	7,358	6,534	6,013	3,864							
FATE	BUICK_CAR	1.8L_L4_N													706																
FATE	BUICK_CAR	2.0L_L4_N										241	566																		
FATE	BUICK_CAR	3.1L_V6_N																											5,906	2,696	2,627
FATE	BUICK_CAR	3.8L_V6_N											343																10,515	3,842	2,227
FATE	BUICK_CAR	5.0L_V8_N																		291											
FATE	BUICK_CAR	5.7L_V8_N																			2,572	1,182	1,550	1,193	1,019						
FATE	CADILLAC_CAR	2.0L_L4_N										785	1,151																		
FATE	CADILLAC_CAR	4.1L_V8_N									6,694	11,453	14,112	23,867	17,132	17,252															
FATE	CADILLAC_CAR	4.5L_V8_N															18,406		428	298	240										
FATE	CADILLAC_CAR	4.6L_V8_N																											9,142	4,564	2,824
FATE	CADILLAC_CAR	5.7L_V8_N																	968	631	349	1,426	1,397	805	792						
FATE	CADILLAC_CAR	6.0L_V8_N								5,496																					
FATE	CADILLAC_TRK	5.7L_V8_N																											4,866		
FATE	CHEVROLET_CAR	2.0L_L4_N										2,361	5,133																		
FATE	CHEVROLET_CAR	3.1L_V6_N																											12,505	9,788	4,321
FATE	CHEVROLET_CAR	3.4L_V6_N																							1,132						
FATE	CHEVROLET_CAR	4.3L_V6_N												1,901	809	531	359														
FATE	CHEVROLET_CAR	4.3L_V8_N																							861						
FATE	CHEVROLET_CAR	5.0L_V8_N									499	705			2,460	1,601	3,047	8,161	3,313	11,011	5,663	1,161									
FATE	CHEVROLET_CAR	5.7L_V8_N									1,536		4,402		3,374	3,697	3,089	5,413	3,586	4,002	3,711	5,169	9,128	11,141	10,370	3,209	6,348				
FATE	CHEVROLET_TRK	1.6L_L4_N																					1,397	1,315							
FATE	CHEVROLET_TRK	2.2L_L4_N																					5,916	10,883							
FATE	CHEVROLET_TRK	2.8L_V6_N													13,922	14,846	8,053	1,658		3,812	3,130	4,625									
FATE	CHEVROLET_TRK	3.4L_V6_N																											4,042	1,876	1,331
FATE	CHEVROLET_TRK	3.8L_V6_N																				439	496	607							
FATE	CHEVROLET_TRK	4.3L_V6_N													11,117	13,623	23,390	36,915	20,890	32,296	26,932	10,014						37,279	42,860	16,142	
FATE	CHEVROLET_TRK	4.8L_V8_N																										5,450	10,801	8,047	
FATE	CHEVROLET_TRK	5.0L_V8_N																											984	369	112
FATE	CHEVROLET_TRK	5.3L_V8_N																										16,796	42,854	29,705	
FATE	CHEVROLET_TRK	5.7L_V8_N														13,171	27,024												14,829	1,692	1,216
FATE	CHEVROLET_TRK	6.0L_V8_N																										2,255	5,023	2,928	
FATE	CHEVROLET_TRK	7.4L_V8_N																	8,382	5,243	5,639	7,754	7,324	7,914	6,179	6,060	6,135	6,612	5,128		
FATE	CHRYSLER_CAR	2.2L_L4_N											800	1,434	702	460															
FATE	CHRYSLER_CAR	3.3L_V6_N																	5,824												
FATE	CHRYSLER_CAR	3.8L_V6_N																		277	1,142	765									
FATE	CHRYSLER_TRK	3.3L_V6_N																	428	281	1,518										
FATE	DODGE/MITS_TRK	2.4L_L4_N																	495	665	449										
FATE	DODGE/MITS_TRK	2.5L_L4_N											836	979	1,614	418	1,244														
FATE	DODGE_CAR	2.0L_L4_N																							8,068						
FATE	DODGE_CAR	2.2L_L4_N											448	2,092	1,834	3,238															
FATE	DODGE_CAR	3.3L_V6_N																	1,559												
FATE	DODGE_TRK	2.5L_L4_N															2,369	3,457	2,078	480	218	158	141	1,449							
FATE	DODGE_TRK	2.5L_L4_T																2,386	293												
FATE	DODGE_TRK	3.3L_V6_N																	10,004	9,027	9,836										
FATE	DODGE_TRK	3.9L_V6_N															5,199	5,916	5,019	2,565	4,711	4,400	5,694	5,329							
FATE	DODGE_TRK	5.2L_V8_N															6,224	7,561	6,119	5,037											
FATE	DODGE_TRK	8.0L_V10_N																					450	1,395							
FATE	FORDTRUCK_TRK	7.5L_V8_N																	885	758	986	399	2,179	2,154	1,652	3,620					
FATE	FORD_CAR	1.9L_L4_N													1,079	2,321	4,147	4,646	2,293												
FATE	FORD_CAR	2.3L_L4_N												7,939	8,272	7,780	11,310	10,705	11,185	10,069	8,323										
FATE	FORD_CAR	2.5L_L4_N													1,815	3,353	1,246	899	169												
FATE	FORD_CAR	3.0L_L4_N																							52	450	357	203			
FATE	FORD_CAR	3.0L_V6_N																								22,125	22,083	15,729	8,600	989	984
FATE	FORD_CAR	3.4L_V8_N																								458	232	159			
FATE	FORD_CAR	3.8L_V6_N											10,741	10,423	12,709	5,394											18,668				
FATE	FORD_CAR	4.6L_V8_N																							8,324	1,070	9,167	5,505			
FATE	FORD_CAR	5.0L_V8_N													4,792	12,247	15,835	14,651	11,942	11,390	6,398	7,672	8,013	9,382							
FATE	FORD_TRK	3.8L_V6_N																												6,658	4,272
FATE	FORD_TRK	4.9L_I6_N														7,885	8,143	9,241													
FATE	FORD_TRK	4.9L_L6_N																	7,815	7,880	8,153	9,509	11,562	12,975	9,706						
FATE	FORD_TRK	5.0L_V8_N												5,587	20,209	12,623	13,558	14,469	14,542	9,671	9,968	9,348	11,901	11,920	16,783	9,267					
FATE	FORD_TRK	5.8L_V8_N															9,462	13,269	13,469	10,527	12,842	13,425	14,695	17,468							
FATE	FORD_TRK	7.5L_V8_N															10,392	16,922	15,337	10,416	9,959	9,019	9,147	10,289	10,004	5,563					

Metering_ECS	Make_CarTrk	Engine	MY74	MY75	MY76	MY77	MY78	MY79	MY80	MY81	MY82	MY83	MY84	MY85	MY86	MY87	MY88	MY89	MY90	MY91	MY92	MY93	MY94	MY95	MY96	MY97	MY98	MY99	MY00	MY01	MY02
FATE	GMC_TRK	2.2L_L4_N																					1,227	2,063							
FATE	GMC_TRK	2.8L_V6_N													2,862	3,512	1,739	285		563	467	530									
FATE	GMC_TRK	4.3L_V6_N													1,857	2,664	4,694	7,613	6,205	10,726	8,783	4,166						10,595	13,312	4,835	
FATE	GMC_TRK	4.8L_V8_N																										2,400	3,958	3,089	
FATE	GMC_TRK	5.0L_V8_N																											372	196	
FATE	GMC_TRK	5.3L_V8_N																										6,472	14,176	8,658	
FATE	GMC_TRK	5.7L_V8_N														4,421	8,874												4,956	575	491
FATE	GMC_TRK	6.0L_V8_N																										587	1,843	2,931	
FATE	GMC_TRK	7.4L_V8_N																	1,607	1,350	1,223	1,927	1,989	2,402	2,424	1,845	1,792	2,141	1,055		
FATE	INFINITI_CAR	2.0L_L4_N																		3,571	1,858	4,095	1,854	3,245							
FATE	ISUZU_CAR	1.5L_L4_N														63	61														
FATE	ISUZU_CAR	1.8L_L4_N											163	65																	
FATE	ISUZU_CAR	1.9L_L4_N										327	888	631	664																
FATE	ISUZU_CAR	2.0L_L4_N												109	268	69	142	72													
FATE	ISUZU_CAR	2.3L_L4_N															495	87													
FATE	ISUZU_TRK	1.9L_L4_N										324	1,259	1,306	1,231	796															
FATE	ISUZU_TRK	2.3L_L4_N													5,911	2,349	1,009	1,415					318	203							
FATE	ISUZU_TRK	2.6L_L4_N																	5,322	2,884	2,924	1,545	1,617	1,657	833	1,113					
FATE	ISUZU_TRK	2.6L_V6_N															4,639	6,146													
FATE	ISUZU_TRK	2.8L_V6_N																1,157	1,949	2,249											
FATE	ISUZU_TRK	3.1L_V6_N																		3,483	5,876										
FATE	ISUZU_TRK	3.2L_V6_N																			2,062	6,443	9,830	11,999							
FATE	JAGUAR_CAR	4.0L_L6_N																						2,927	2,356	1,878					
FATE	JAGUAR_CAR	4.0L_V6_N																	2,964	1,764											
FATE	JEEP_TRK	4.0L_V6_N																						24,589							
FATE	KIA_CAR	2.0L_L4_N																							1,221	1,979	1,537	2,158	4,653		
FATE	LINCOLN_CAR	3.0L_V6_N																											1,679	1,027	519
FATE	LINCOLN_CAR	4.6L_V8_N																							3,475	4,179	3,738	1,339			
FATE	LINCOLN_CAR	5.0L_V8_N								1,325		2,780	6,161	6,047	7,286	5,973	10,851	7,783	10,945	938	474										
FATE	MAZDA_CAR	1.3L_ROT_N														5,287	4,987														
FATE	MAZDA_CAR	1.6L_L4_N														5,513															
FATE	MAZDA_CAR	2.0L_L4_N													8,540	7,334															
FATE	MAZDA_TRK	2.2L_L4_N																	7,807		3,263	2,401									
FATE	MAZDA_TRK	2.3L_L4_N																					3,253	2,146							
FATE	MAZDA_TRK	2.6L_L4_N																	2,036	3,559	1,939	662	406								
FATE	MAZDA_TRK	3.0L_V6_N																	7,375				3,666	380							
FATE	MAZDA_TRK	4.0L_V6_N																		1,623	1,186	382	2,944	133							
FATE	MERCEDES_CAR	2.2L_L4_N																							3,098						
FATE	MERCEDES_CAR	2.6L_L6_N																	3,605	3,679	2,306	2,345									
FATE	MERCEDES_CAR	2.6L_V6_N																												1,726	2,595
FATE	MERCEDES_CAR	2.8L_L6_N						1,022																	2,924	2,991					
FATE	MERCEDES_CAR	3.0L_L6_N																	7,433	7,417	4,647										
FATE	MERCEDES_CAR	3.2L_L6_N																						6,602	5,973	13,336	857	1,595			
FATE	MERCEDES_CAR	3.2L_V6_N																									1,368	12,547	11,176	6,251	3,936
FATE	MERCEDES_CAR	4.2L_V8_N													3,563	4,176	1,914	2,132	1,568	1,819			927	2,560	822						
FATE	MERCEDES_CAR	4.3L_V8_N																											8,521	3,889	2,045
FATE	MERCEDES_CAR	4.5L_V8_N						3,307																							
FATE	MERCEDES_CAR	5.0L_V8_N																	622	1,421					1,523	2,163	2,569		6,826	2,804	1,594
FATE	MERCEDES_CAR	5.6L_V8_N													5,295	5,562	4,661	4,261	1,616	1,965											
FATE	MERCEDES_CAR	6.0L_V12_N																							173	261	122				
FATE	MERCEDES_CAR	6.0L_V8_N																							117	201	199		90	26	
FATE	MERCEDES_TRK	3.2L_V6_N																										6,646	8,775	2,724	1,308
FATE	MERCEDES_TRK	5.0L_V8_N																													528
FATE	MERCURY_CAR	2.3L_L4_N												2,493	1,844	2,114	2,575	3,714	2,840	2,236	1,860										
FATE	MERCURY_CAR	3.0L_V6_N																								4,645	5,174	3,316		127	
FATE	MERCURY_CAR	3.8L_V6_N											3,905	4,701	4,268	2,678															
FATE	MERCURY_CAR	5.0L_V8_N														4,615	4,693	3,016	1,725	2,989	516	671									
FATE	MERCURY_TRK	5.0L_V8_N																								4,404					
FATE	MITSUBISHI_CAR	1.6L_L4_T												117	122	134	59														
FATE	MITSUBISHI_CAR	1.8L_L4_N																				3,222	3,272	1,650							
FATE	MITSUBISHI_CAR	1.8L_L4_T											114	107	83	111	93														
FATE	MITSUBISHI_CAR	2.0L_L4_N																4,489													
FATE	MITSUBISHI_CAR	2.4L_L4_N												856																	
FATE	MITSUBISHI_CAR	2.6L_L4_N										233																			

Metering_ECS	Make_CarTrk	Engine	MY74	MY75	MY76	MY77	MY78	MY79	MY80	MY81	MY82	MY83	MY84	MY85	MY86	MY87	MY88	MY89	MY90	MY91	MY92	MY93	MY94	MY95	MY96	MY97	MY98	MY99	MY00	MY01	MY02
FATE	MITSUBISHI_CAR	2.6L_L4_T											181	294	350	696	345														
FATE	MITSUBISHI_CAR	3.0L_V6_N																				1,075	1,227	569							
FATE	MITSUBISHI_TRK	2.6L_L4_N										216																			
FATE	MITSUBISHI_TRK	3.5L_V6_N																					908	1,456							
FATE	NISSAN_CAR	1.6L_L4_N														46,367	27,795	36,019	19,450												
FATE	NISSAN_CAR	1.8L_L4_N															1,780	161													
FATE	NISSAN_CAR	2.0L_L4_N														12,675	4,620	1,826		2,697	1,684	1,299	211								
FATE	NISSAN_CAR	2.4L_L4_N																11,416	7,278	11,685	9,242	21,160	16,188	20,366							
FATE	NISSAN_CAR	3.0L_V6_N													14,490	28,749			6,121	2,798											
FATE	NISSAN_CAR	3.0L_V6_T													920	472			1,239	948	373	319	156								
FATE	NISSAN_TRK	2.4L_L4_N													35,720	18,888	11,331	13,943	14,294	15,912	10,177	15,220	11,834	14,899	11,240					7,824	4,030
FATE	NISSAN_TRK	3.0L_V6_N													6,145	8,971	6,351	4,597				7,339									
FATE	OLDSMOBILE_CAR	1.8L_L4_N													459																
FATE	OLDSMOBILE_CAR	2.0L_L4_N										135	312																		
FATE	OLDSMOBILE_CAR	3.4L_V6_N																							134			3,118			
FATE	OLDSMOBILE_CAR	3.8L_V6_N											204																		
FATE	OLDSMOBILE_CAR	4.0L_V8_N																						2,785						269	
FATE	OLDSMOBILE_CAR	5.0L_V8_N																		377	27										
FATE	OLDSMOBILE_TRK	3.4L_V6_N																											1,243	410	97
FATE	OLDSMOBILE_TRK	3.8L_V6_N																				434	764	754							
FATE	OLDSMOBILE_TRK	4.3L_V6_N																		802	744	431						687	731	154	
FATE	PLYM/MITS_CAR	1.6L_L4_N																1,934													
FATE	PLYM/MITS_CAR	1.6L_L4_T											52	67	108	114	56	57													
FATE	PLYM/MITS_CAR	2.0L_L4_N																384	42	246											
FATE	PLYMOUTH_CAR	1.8L_L4_N																	1,153	443	600										
FATE	PLYMOUTH_CAR	2.0L_L4_N																							8,901						
FATE	PLYMOUTH_CAR	2.2L_L4_N												1,114	1,617	2,564															
FATE	PLYMOUTH_CAR	3.3L_V6_N																	1,600												
FATE	PLYMOUTH_TRK	2.5L_L4_N															1,470	2,858	1,164												
FATE	PLYMOUTH_TRK	2.5L_L4_T																2,289	282												
FATE	PLYMOUTH_TRK	3.3L_V6_N																	8,574	7,039	6,878										
FATE	PONTIAC_CAR	1.6L_L4_N															2,912														
FATE	PONTIAC_CAR	1.8L_L4_N													1,311																
FATE	PONTIAC_CAR	3.1L_V6_N																											1,959	1,642	1,883
FATE	PONTIAC_CAR	3.4L_V6_N																							109			8,039			
FATE	PONTIAC_CAR	5.0L_V8_N									299	388			1,067	782	1,217	996	400	1,404	937										
FATE	PONTIAC_CAR	5.7L_V8_N														569	672	706	176	253		846	1,874	1,758	995	1,119			1,156		
FATE	PONTIAC_TRK	3.4L_V6_N																											2,015	1,797	708
FATE	PONTIAC_TRK	3.8L_V6_N																				864	1,917	1,724							
FATE	ROLLSROYCE_CAR	6.8L_V8_N								214	254	111	232	300	236	219	225	251	107	118											
FATE	SATURN_CAR	1.9L_L4_N																										26,036	14,466	7,205	5,569
FATE	STERLING_CAR	2.5L_V6_N														1,560	907														
FATE	TOYOTA_CAR	1.5L_L4_N																	913	1,722				16,553							
FATE	TOYOTA_CAR	1.6L_L4_N														271	126	483													
FATE	TOYOTA_CAR	1.8L_L4_N																				1,460	3,122	2,165							
FATE	TOYOTA_TRK	2.2L_L4_N													9,126	7,635	2,799														
FATE	TOYOTA_TRK	2.3L_L4_N														41,687	37,187	37,889													
FATE	TOYOTA_TRK	2.4L_L4_N																		49,313	36,195	39,683	40,124	16,806	17,218						
FATE	TOYOTA_TRK	2.4L_L4_S																							3,295						
FATE	TOYOTA_TRK	3.0L_V6_N															4,877	13,727	24,627	21,356	18,326	20,669	23,217	30,653							
FATE	TOYOTA_TRK	4.0L_L6_N														801	952	1,171													
FATE	TOYOTA_TRK	4.2L_L6_N																	445	2,486	1,742										
FATE	TOYOTA_TRK	4.5L_L6_N																				1,807	3,400	1,621							
FATE	VOLVO_CAR	2.4L_L5_N																							5,985						
FATE	VW_TRK	2.1L_H4_N																	2,905	310											
FATE	VW_TRK	2.8L_V6_N																								403					
FATN	ACURA_CAR	3.0L_V6_N																		757											
FATN	ACURA_CAR	3.2L_V6_N																		573											
FATN	AUDI_CAR	1.8L_L4_T																											3,330	3,926	2,343
FATN	AUDI_CAR	2.7L_V6_N																											1,702	1,840	254
FATN	AUDI_CAR	2.8L_V6_N																											2,423	1,673	
FATN	AUDI_CAR	4.2L_V8_N																											769	435	173
FATN	BMW_CAR	2.3L_L6_N																										1,090	2,461		
FATN	BMW_CAR	2.5L_L6_N																									2,510	7,659	13,358	8,375	6,033

Metering_ECS	Make_CarTrk	Engine	MY74	MY75	MY76	MY77	MY78	MY79	MY80	MY81	MY82	MY83	MY84	MY85	MY86	MY87	MY88	MY89	MY90	MY91	MY92	MY93	MY94	MY95	MY96	MY97	MY98	MY99	MY00	MY01	MY02
FATN	BMW_CAR	2.8L_L6_N																							6,673	15,477	13,061	9,583	13,590		
FATN	BMW_CAR	2.8L_V6_N																										781	699		
FATN	BMW_CAR	3.0L_L6_N																						1,986						12,579	3,327
FATN	BMW_CAR	3.2L_L6_N																											1,003	1,386	1,221
FATN	BMW_CAR	4.4L_V8_N																											1,959	3,138	393
FATN	BMW_CAR	5.0L_V8_N																											809	463	281
FATN	BMW_TRK	3.0L_L6_N																													1,475
FATN	BMW_TRK	4.4L_V8_N																													588
FATN	BMW_TRK	4.6L_V8_N																													112
FATN	CADILLAC_CAR	3.0L_V6_N																								2,637	2,728	1,339	1,233	521	
FATN	CADILLAC_CAR	4.5L_V8_N																22,321													
FATN	CHEVROLET_CAR	5.7L_V8_N																										5,880	6,116	3,318	2,627
FATN	DODGE_TRK	8.0L_V10_N																							2,252	1,131	1,228	1,647	438	348	
FATN	FERRARI_CAR	2.9L_V8_N									29	115	88	170																	
FATN	FERRARI_CAR	3.2L_V8_N													168	149	158	102													
FATN	FERRARI_CAR	3.4L_V8_N																	158	90	60		132	46							
FATN	FERRARI_CAR	3.5L_V8_N																						182	88						
FATN	FERRARI_CAR	4.9L_H12_N												31	62	77	89	55	136	25	66	30									
FATN	FERRARI_CAR	5.5L_V12_N																						53							
FATN	HONDA_CAR	2.0L_L4_N																											1,557	851	606
FATN	HYUNDAI_CAR	1.5L_L4_N																				631	857	4,352							
FATN	HYUNDAI_CAR	1.8L_L4_N																				1,321	1,548	1,805							
FATN	ISUZU_CAR	1.6L_L4_N																	547	2,087	73										
FATN	ISUZU_CAR	1.6L_L4_T																		70											
FATN	ISUZU_CAR	1.8L_L4_N																			95										
FATN	JAGUAR_CAR	3.6L_L6_N															4,253														
FATN	JAGUAR_CAR	4.2L_L6_N								305	854	1,092	1,695	2,604	2,968	2,293															
FATN	JAGUAR_CAR	5.3L_V12_N									144	189	314	441	690	514	829	537	1,271		348										
FATN	JAGUAR_CAR	6.0L_V12_N																					405	184	77						
FATN	LANDROVER_TRK	4.0L_V8_N																											4,084	1,744	1,630
FATN	LANDROVER_TRK	4.6L_V8_N																											925	710	336
FATN	MAZDA_CAR	1.3L_ROT_N											2,545	4,842	4,667																
FATN	MAZDA_CAR	2.2L_L4_N															10,306														
FATN	MERCEDES_CAR	2.3L_L4_N																											1,414	2,867	1,488
FATN	MERCEDES_CAR	2.7L_L6_N								332																					
FATN	MERCEDES_CAR	2.8L_L6_N							457																						
FATN	MERCEDES_CAR	3.8L_V8_N								2,316	2,877	3,424	3,375	4,963																	
FATN	MERCEDES_CAR	4.2L_V8_N																								5,390					
FATN	MERCEDES_CAR	4.5L_V8_N							2,319																						
FATN	MERCEDES_CAR	5.0L_V8_N											1,377	2,572														970			
FATN	MITSUBISHI_TRK	3.0L_V6_N																	2,440	1,636	1,177	877	1,011	2,443							
FATN	OLDSMOBILE_CAR	3.5L_V6_N																										1,872			
FATN	PONTIAC_CAR	5.7L_V8_N																										1,193		454	417
FATN	PORSCHE_CAR	2.5L_H6_N																								1,293	1,855	3,252			
FATN	PORSCHE_CAR	2.7L_H6_N																											1,854	794	412
FATN	PORSCHE_CAR	3.2L_H6_N																											1,177	608	292
FATN	PORSCHE_CAR	3.4L_H6_N																										4,053	2,130	1,342	
FATN	PORSCHE_CAR	3.6L_H6_N																							1,774	1,719	806			591	1,499
FATN	PORSCHE_CAR	3.6L_H6_T																								287					
FATN	PORSCHE_CAR	5.0L_V8_N																	93	88		32	31								
FATN	SAAB_CAR	2.3L_L4_N																							954	908	470				
FATN	SAAB_CAR	2.3L_L4_T																							125	274					
FATN	SAAB_CAR	2.3L_V6_N																							230						
FATN	SAAB_CAR	2.5L_V6_N																							200	27					
FATN	SATURN_CAR	2.2L_L4_N																													1,647
FATN	VOLVO_CAR	2.4L_L5_N																								2,947					
FATN	VOLVO_CAR	2.4L_L5_T																								2,297					
FATN	VOLVO_CAR	2.8L_L6_T																										1,696	1,950	565	
FATN	VOLVO_CAR	2.9L_L6_N																							3,161	3,420	2,603		2,546	1,059	468
FATN	VOLVO_CAR	2.9L_L6_T																										1,931			
FATN	VW_CAR	1.8L_L4_T																											9,062	5,161	4,933
FATN	VW_CAR	2.0L_L4_N																							20,584	17,508	24,315	36,017	7,047	10,986	5,963
FATN	VW_CAR	2.8L_V6_N																							1,031	2,104	2,532	1,818	6,339	5,287	1,564
FATN	VW_TRK	2.8L_V6_N																										609	512		

Metering_ECS	Make_CarTrk	Engine	MY74	MY75	MY76	MY77	MY78	MY79	MY80	MY81	MY82	MY83	MY84	MY85	MY86	MY87	MY88	MY89	MY90	MY91	MY92	MY93	MY94	MY95	MY96	MY97	MY98	MY99	MY00	MY01	MY02
FATN	VW_TRK	2.9L_V6_N																												260	392
FNTE	ACURA_CAR	1.6L_L4_N													2,964	10,766	8,999	9,491													
FNTE	ACURA_CAR	1.8L_L4_N																		9,378											
FNTE	ACURA_CAR	2.2L_L4_N																								4,426					
FNTE	ACURA_CAR	2.3L_L4_N																									1,764	1,641			
FNTE	ACURA_CAR	2.5L_L5_N																						97	3,967	1,224	1,127				
FNTE	ACURA_CAR	3.0L_V6_N																							175	3,884	2,490	2,595			
FNTE	ACURA_CAR	3.2L_V6_N																							2,383	2,204	1,767	7,879	10,199	5,258	2,799
FNTE	ACURA_CAR	3.5L_V6_N																							2,340	2,293	1,838	1,680	2,184	230	553
FNTE	ACURA_TRK	3.2L_V6_N																							460	159					
FNTE	ACURA_TRK	3.5L_V6_N																												1,876	1,129
FNTE	AUDI_CAR	2.8L_V6_N																							2,958	1,977	4,980				
FNTE	BUICK_CAR	1.8L_L4_N									92	331	1,007	577																	
FNTE	BUICK_CAR	2.0L_L4_N												518	555	889	587	704													
FNTE	BUICK_CAR	2.4L_L4_N																							433	1,069					
FNTE	BUICK_CAR	2.5L_L4_N									1,067	926	1,141	4,111	4,939	2,942	1,056	1,429	2,509	1,641											
FNTE	BUICK_CAR	2.8L_V6_N												1,119		1,163	7,678	2,738													
FNTE	BUICK_CAR	3.0L_V6_N												1,000	1,779	1,453	831														
FNTE	BUICK_CAR	3.1L_V6_N																2,131	2,096	1,571	1,475	859	6,634	5,997	5,844	3,869	7,422	6,204			
FNTE	BUICK_CAR	3.8L_V6_N												6,340	11,936	13,326	11,124	10,582	10,727	17,513	13,761	13,993	13,312	13,590	12,469	11,793	10,900	7,689			
FNTE	BUICK_CAR	3.8L_V6_S																			897	968	849	2,519	1,316	2,550	3,396	2,143	1,113	218	
FNTE	CADILLAC_CAR	2.0L_L4_N												373	85																
FNTE	CADILLAC_CAR	2.8L_V6_N												575	1,467	1,212	542														
FNTE	CADILLAC_CAR	4.5L_V8_N																	20,782												
FNTE	CADILLAC_CAR	4.6L_V8_N																				3,834	3,493	2,799	13,392	10,898	10,562	10,855			
FNTE	CADILLAC_CAR	4.9L_V8_N																		15,067	16,456	9,076	4,623	3,580							
FNTE	CADILLAC_TRK	5.3L_V8_N																													1,224
FNTE	CADILLAC_TRK	5.7L_V8_N																										2,507			
FNTE	CADILLAC_TRK	6.0L_V8_N																													3,970
FNTE	CHEV/SUZUKI_CAR	1.0L_L3_N														486		3,147	3,241	1,397	558	603									
FNTE	CHEVROLET_CAR	1.0L_L3_N																	2,014	6,743	6,895	5,379	8,996	6,774	5,646	12,288	1,085	911	581		
FNTE	CHEVROLET_CAR	1.6L_L4_N																312	18,294	12,530	6,474	10,483	9,288	7,954	5,549						
FNTE	CHEVROLET_CAR	1.8L_L4_N																				3,030	2,604	1,904	1,048	546	4,729				
FNTE	CHEVROLET_CAR	2.0L_L4_N												4,822	5,231	5,013	8,224	7,696													
FNTE	CHEVROLET_CAR	2.2L_L4_N																	9,154	9,877	5,068	6,672	8,578		14,640	15,205	12,912				
FNTE	CHEVROLET_CAR	2.4L_L4_N																							1,571	3,639	4,828				
FNTE	CHEVROLET_CAR	2.5L_L4_N									1,226	987	1,700	2,619	2,838	3,822	2,398	2,271	1,010	469											
FNTE	CHEVROLET_CAR	2.8L_V6_N												8,534	9,835	10,624	23,322	19,009													
FNTE	CHEVROLET_CAR	3.1L_V6_N																	17,348	15,557	15,534	11,118	8,241	13,937	14,221	17,223	21,396	15,662			
FNTE	CHEVROLET_CAR	3.4L_V6_N																		380	611	388		2,301		442			5,449	4,050	3,425
FNTE	CHEVROLET_CAR	3.8L_V6_N																							4,377	4,627	6,193	4,173	9,053	3,981	2,006
FNTE	CHEVROLET_CAR	4.3L_V8_N																					1,510	934							
FNTE	CHEVROLET_TRK	1.6L_L4_N																	952	1,289	1,295	1,554	635	344	2,231	1,111	877	289	120		
FNTE	CHEVROLET_TRK	2.0L_L4_N																										1,496	1,968	517	342
FNTE	CHEVROLET_TRK	2.2L_L4_N																							10,659	7,983	13,156	8,187	5,441		
FNTE	CHEVROLET_TRK	2.5L_L4_N												2,569	2,212	3,316	4,496	4,355	1,271	5,338	1,523	953									
FNTE	CHEVROLET_TRK	3.1L_V6_N																	4,256	1,825	772	973	2,128	3,787							
FNTE	CHEVROLET_TRK	3.4L_V6_N																							1,592	4,420	4,594	3,771			
FNTE	CHEVROLET_TRK	4.3L_V6_N																				20,419	38,866	48,249	38,794	46,434	45,236				8,703
FNTE	CHEVROLET_TRK	4.8L_V8_N																													8,027
FNTE	CHEVROLET_TRK	5.0L_V8_N														6,483	4,299	3,717	2,272	2,220	2,046	2,113	2,827	4,128	6,831	4,384	6,541	925			
FNTE	CHEVROLET_TRK	5.3L_V8_N																													17,898
FNTE	CHEVROLET_TRK	5.7L_V8_N																34,010	33,514	24,505	26,509	30,920	43,475	49,212	38,616	48,275	39,435	61,192			
FNTE	CHEVROLET_TRK	6.0L_V8_N																													2,205
FNTE	CHEVROLET_TRK	8.1L_V8_N																												1,755	956
FNTE	CHRYSLER_CAR	2.0L_L4_N																						1,839	224	225	125				
FNTE	CHRYSLER_CAR	2.4L_L4_N																							1,431	462	213		501	623	947
FNTE	CHRYSLER_CAR	2.5L_L4_N																	538	246	663				2,311	2,668	3,227	2,148	851		
FNTE	CHRYSLER_CAR	2.5L_L4_T																	311	97	47										
FNTE	CHRYSLER_CAR	2.5L_V6_N																						4,604	6,223	6,017	6,893	5,790	6,089	653	203
FNTE	CHRYSLER_CAR	2.7L_V6_N																									814	2,044	1,462	3,148	2,182
FNTE	CHRYSLER_CAR	3.0L_V6_N															3,917	5,492	4,975	4,474	3,906	3,351	4,330	3,042							
FNTE	CHRYSLER_CAR	3.2L_V6_N																									2,114	2,558	1,222	261	
FNTE	CHRYSLER_CAR	3.3L_V6_N																		3,901	1,952	3,028	2,451	1,296	1,079						

Metering_ECS	Make_CarTrk	Engine	MY74	MY75	MY76	MY77	MY78	MY79	MY80	MY81	MY82	MY83	MY84	MY85	MY86	MY87	MY88	MY89	MY90	MY91	MY92	MY93	MY94	MY95	MY96	MY97	MY98	MY99	MY00	MY01	MY02
FNTE	CHRYSLER_CAR	3.5L_V6_N																				2,054	8,349	4,563	3,829	4,218		9,931	5,494	2,431	1,047
FNTE	CHRYSLER_TRK	2.4L_L4_N																												6,907	6,649
FNTE	CHRYSLER_TRK	3.3L_V6_N																							1,107	393	95	130	1,745		
FNTE	CHRYSLER_TRK	3.8L_V6_N																					3,470	1,045	8,936	6,384	4,549	4,383	3,016	1,450	707
FNTE	DAEWOO_CAR	1.6L_L4_N																										1,850	4,015	1,508	254
FNTE	DAEWOO_CAR	2.0L_L4_N																										1,906	3,147	925	398
FNTE	DAEWOO_CAR	2.2L_L4_N																									93	3,222	3,198	936	439
FNTE	DATSUN_CAR	2.2L_L4_T									2,333																				
FNTE	DATSUN_CAR	2.4L_V6_N								1,397	2,738	4,200																			
FNTE	DATSUN_CAR	2.8L_V6_N								4,291	3,831	3,523																			
FNTE	DATSUN_CAR	2.8L_V6_T								657	853	875																			
FNTE	DODGE/MITS_CAR	1.5L_L4_N																2,798	808	1,462	771	103									
FNTE	DODGE/MITS_CAR	1.8L_L4_N																				251	162								
FNTE	DODGE/MITS_CAR	2.0L_L4_N											281	416	808	775	392														
FNTE	DODGE/MITS_CAR	2.6L_L4_T											82	77	146																
FNTE	DODGE/MITS_CAR	3.0L_V6_N																		2,288	1,410	473	648	231							
FNTE	DODGE/MITS_CAR	3.0L_V6_T																		359	369	74	68								
FNTE	DODGE_CAR	2.0L_L4_N																						14,375	1,134	8,397	9,721	3,813			
FNTE	DODGE_CAR	2.2L_L4_N															4,367	3,057	1,429	1,091	996	1,237	950								
FNTE	DODGE_CAR	2.2L_L4_T												1,851						47											
FNTE	DODGE_CAR	2.4L_L4_N																						1,129	3,714	4,900	5,756	4,265	5,128	3,495	2,611
FNTE	DODGE_CAR	2.5L_L4_N																	3,233	4,039	2,346	3,812	3,870	457	1,044	1,006	1,112	892	252		
FNTE	DODGE_CAR	2.5L_L4_T																	338	337	50										
FNTE	DODGE_CAR	2.5L_V6_N																						1,490	1,020	792	1,610	914	2,123	621	261
FNTE	DODGE_CAR	2.7L_V6_N																									3,167	9,007	8,168	7,382	5,714
FNTE	DODGE_CAR	3.0L_V6_N															1,583	3,076	3,188	2,287	1,499	2,048	1,180	246							
FNTE	DODGE_CAR	3.2L_V6_N																									2,037	2,193	1,817	469	
FNTE	DODGE_CAR	3.3L_V6_N																		3,868	2,656	3,233	4,863	4,865	1,958	2,764					
FNTE	DODGE_CAR	3.5L_V6_N																				1,698	2,762	2,600	4,992	5,532					422
FNTE	DODGE_CAR	8.0L_V10_N																			27	144	323	203							
FNTE	DODGE_TRK	2.4L_L4_N																										4,251	4,213	600	465
FNTE	DODGE_TRK	2.5L_L4_N																				1,126	1,160	1,310							
FNTE	DODGE_TRK	3.0L_V6_N														5,252	11,465	10,797	6,796	3,287	5,428	8,266	8,983	7,655	9,024	1,597	1,459	401	648		
FNTE	DODGE_TRK	3.3L_V6_N																							12,643	17,238	15,789	12,651	15,933		
FNTE	DODGE_TRK	3.8L_V6_N																					2,495	886	7,272	4,965	3,522	1,919	1,357	697	501
FNTE	DODGE_TRK	5.2L_V8_N																			6,174	4,605	10,410	8,437							
FNTE	EAGLE_CAR	1.5L_L4_N																1,117	383	343	304										
FNTE	EAGLE_CAR	1.8L_L4_N																				610	478	76							
FNTE	EAGLE_CAR	2.0L_L4_N																		501	730	276	169								
FNTE	EAGLE_CAR	2.2L_L4_T																		192	294										
FNTE	EAGLE_CAR	2.4L_L4_N																				120									
FNTE	EAGLE_CAR	3.0L_V6_N																1,371													
FNTE	EAGLE_CAR	3.3L_V6_N																				692	415	586	117						
FNTE	EAGLE_CAR	3.5L_V6_N																				1,477	735	881	390	234					
FNTE	FORD/MAZDA_CAR	2.0L_L4_N																				5,251	3,515	2,922	1,454	798					
FNTE	FORD/MAZDA_CAR	2.2L_L4_N																13,939	4,028	3,483	2,071										
FNTE	FORD/MAZDA_CAR	2.2L_L4_T																2,626	1,165	256	104										
FNTE	FORD/MAZDA_CAR	2.5L_V6_N																				3,811	1,982	1,137	667	358					
FNTE	FORD/MAZDA_CAR	3.0L_V6_N																	3,122	1,750	834										
FNTE	FORDTRUCK_TRK	6.8L_V10_N																										5,369	1,249		
FNTE	FORD_CAR	1.3L_L4_N																							3,553	4,013					
FNTE	FORD_CAR	1.9L_L4_N														8,972	11,956	13,115	8,791	20,126	9,733	32,228	24,889	30,466	10,478						
FNTE	FORD_CAR	2.0L_L4_N																								25,335	19,604	13,897	15,957	11,522	11,291
FNTE	FORD_CAR	2.3L_L4_N														3,334	4,309	6,805	2,482	2,769	2,789	12,098	6,371								
FNTE	FORD_CAR	2.3L_L4_T										483	1,044	1,196	1,504	1,619	1,930														
FNTE	FORD_CAR	2.5L_V6_N																						3,931	1,943	834	5,634	3,789	2,123		
FNTE	FORD_CAR	3.0L_L4_N																				1,502	1,348	892	846						
FNTE	FORD_CAR	3.0L_V6_N													8,755	15,067	15,680	17,088	18,142	16,215	17,332	11,103	13,560	19,989	26,520	2,001		8,003	10,932	10,750	6,287
FNTE	FORD_CAR	3.2L_V6_N																				1,189	806	569							
FNTE	FORD_CAR	3.8L_V6_N															8,583	22,743	17,673	11,820	18,122	35,015	22,585	19,772	15,647	13,145					
FNTE	FORD_CAR	3.8L_V6_S																				550	348	303							
FNTE	FORD_CAR	4.6L_V8_N																			8,832	5,786	17,107	22,056	15,255	19,702	5,007	5,723	11,804	5,130	2,868
FNTE	FORD_TRK	2.3L_I4_N												4,294	6,835	6,750	10,257	8,270													
FNTE	FORD_TRK	2.3L_L4_N																	6,647	5,473	7,573	10,887	20,168	10,962	16,102	18,375				745	1,436

Metering_ECS	Make_CarTrk	Engine	MY74	MY75	MY76	MY77	MY78	MY79	MY80	MY81	MY82	MY83	MY84	MY85	MY86	MY87	MY88	MY89	MY90	MY91	MY92	MY93	MY94	MY95	MY96	MY97	MY98	MY99	MY00	MY01	MY02
FNTE	FORD_TRK	2.5L_L4_N																									13,313	8,610	8,321	1,477	
FNTE	FORD_TRK	2.9L_V6_N													18,233	17,996															
FNTE	FORD_TRK	3.0L_V6_N																					18,152	14,490	15,975	10,515	20,368	18,615	18,305	7,508	4,505
FNTE	FORD_TRK	3.8L_V6_N																						30,073	18,079	2,391	22,585	15,339	16,504		
FNTE	FORD_TRK	4.0L_V6_N																					57,108	36,535	43,651	42,179	53,466	44,310	32,582	24,306	21,004
FNTE	FORD_TRK	4.2L_V6_N																								19,860	17,417	20,471	16,546	8,950	4,586
FNTE	FORD_TRK	4.6L_V8_N																								41,363	37,734	28,925	25,949	16,268	9,362
FNTE	FORD_TRK	5.0L_V8_N																									8,186	4,624	4,372	584	
FNTE	FORD_TRK	5.4L_V8_N																								34,247	37,739	49,435	49,955	25,438	11,638
FNTE	FORD_TRK	5.8L_V8_N																							13,426	3,031					
FNTE	FORD_TRK	6.8L_V10_N																								3,712	3,514	11,297	16,128	5,781	3,523
FNTE	GMC_TRK	2.2L_L4_N																							3,732	1,665	3,734	1,800	1,090		
FNTE	GMC_TRK	2.5L_L4_N												815	748	647	926	1,039	271	1,054	275	224									
FNTE	GMC_TRK	4.3L_V6_N																				6,734	12,269	14,865	11,903	14,894	13,358				1,726
FNTE	GMC_TRK	4.8L_V8_N																													2,313
FNTE	GMC_TRK	5.0L_V8_N														1,354	833	684	610	937	1,261	1,066	1,327	3,659	2,127	1,252	3,271	549			
FNTE	GMC_TRK	5.3L_V8_N																													4,098
FNTE	GMC_TRK	5.7L_V8_N																10,117	11,910	8,110	9,740	11,822	15,497	19,117	14,402	17,525	12,964	22,966			
FNTE	GMC_TRK	6.0L_V8_N																													2,408
FNTE	GMC_TRK	8.1L_V8_N																												562	343
FNTE	HONDA_CAR	1.5L_L4_N															2,021	11,911	33,857	41,482											
FNTE	HONDA_CAR	1.6L_L4_N																148							1,222	3,451	3,014	1,322	1,308		
FNTE	HONDA_CAR	1.7L_L4_N																												22,258	13,437
FNTE	HONDA_CAR	1.8L_L4_N												2,615																	
FNTE	HONDA_CAR	2.0L_L4_N												1,036	18,955	20,140	28,124	33,523	4,918	5,341						10,316	14,476				
FNTE	HONDA_CAR	2.2L_L4_N																	72,469	82,910	64,518	51,316	68,811	53,499	62,764	63,023	5,850	2,500	2,341	1,050	
FNTE	HONDA_CAR	2.3L_L4_N																							1,166		48,080	45,642	47,237	15,662	11,081
FNTE	HONDA_CAR	3.0L_V6_N																									18,686	15,391	24,036	6,660	4,242
FNTE	HONDA_TRK	2.6L_L4_N																					211	495	162						
FNTE	HONDA_TRK	3.2L_V6_N																					3,292	4,339	2,113	2,669		3,797	2,818	1,208	286
FNTE	HONDA_TRK	3.5L_V6_N																										7,517	18,437	3,913	3,013
FNTE	HYUNDAI_CAR	1.5L_L4_N																	7,399	7,830	3,146	2,867	3,732								
FNTE	HYUNDAI_CAR	1.6L_L4_N																			2,199	353	637	770							
FNTE	HYUNDAI_CAR	2.0L_L4_N																			533	507		1,289	467	1,066					
FNTE	HYUNDAI_CAR	2.4L_L4_N																3,249	1,039	818								397	927	827	994
FNTE	HYUNDAI_CAR	3.0L_V6_N																	1,102	824	672	583		1,173	222	388	244				
FNTE	INFINITI_CAR	2.0L_L4_N																							2,983			3,494	2,027	405	619
FNTE	INFINITI_CAR	3.0L_V6_N																	1,683	1,794	507	6,134	4,220	3,833	7,290	6,200	6,042	5,015	6,014		
FNTE	INFINITI_CAR	3.3L_V6_N																								2,351	2,906	3,969	1,331		
FNTE	INFINITI_CAR	4.1L_V8_N																								2,414	1,316	1,272	630	146	
FNTE	INFINITI_CAR	4.5L_V8_N																	2,481	3,601	2,234	870	3,923	1,669	915						
FNTE	ISUZU_TRK	2.2L_L4_N																							591	201	1,832	1,202	486	326	192
FNTE	ISUZU_TRK	2.3L_L4_N																									182	55			
FNTE	ISUZU_TRK	3.2L_V6_N																							6,545	5,119	5,962	7,322	3,550	2,552	558
FNTE	ISUZU_TRK	3.5L_V6_N																									2,058	2,352	1,823	800	774
FNTE	JAGUAR_CAR	3.0L_V6_N																											5,770	1,778	
FNTE	JAGUAR_CAR	4.0L_V8_N																							605	2,075					
FNTE	JEEP_TRK	150CI_L4_N													3,728	1,850	1,650														
FNTE	JEEP_TRK	2.5L_L4_N																2,880	3,044												
FNTE	JEEP_TRK	242CI_I6_N														11,991	18,172														
FNTE	JEEP_TRK	4.0L_V6_N																21,580	15,436												
FNTE	JEEP_TRK	5.2L_V8_N																				10,893	11,818	11,704							
FNTE	KIA_CAR	1.6L_L4_N																					3,935	5,518	710	1,662					
FNTE	KIA_CAR	1.8L_L4_N																						1,090	3,408	1,690					
FNTE	LEXUS_CAR	2.5L_V6_N																	5,268	5,045											
FNTE	LEXUS_CAR	3.0L_L6_N																			2,421	5,497	3,285	3,106	1,088	933					
FNTE	LEXUS_CAR	3.0L_V6_N																			9,667	7,706	6,262	6,819	7,587	11,663	9,753	24,419			
FNTE	LEXUS_CAR	4.0L_V8_N																	9,459	10,442	12,734	7,023	4,979	6,646	5,275	4,566					
FNTE	LEXUS_CAR	4.5L_L6_N																							1,069	1,644					
FNTE	LEXUS_CAR	4.7L_V8_N																									1,169				
FNTE	LINCOLN_CAR	3.8L_V6_N															2,442	4,688	4,450	3,015	2,184	1,318	2,074								
FNTE	LINCOLN_CAR	3.9L_V8_N																											4,010	1,930	1,094
FNTE	LINCOLN_CAR	4.6L_V8_N																		8,054	6,648	9,936	8,733	10,937	4,941	5,470	4,989	5,085	5,841	2,864	1,296
FNTE	LINCOLN_TRK	5.4L_V8_N																									9,769	6,850	6,243	3,653	1,552

Metering_ECS	Make_CarTrk	Engine	MY74	MY75	MY76	MY77	MY78	MY79	MY80	MY81	MY82	MY83	MY84	MY85	MY86	MY87	MY88	MY89	MY90	MY91	MY92	MY93	MY94	MY95	MY96	MY97	MY98	MY99	MY00	MY01	MY02
FNTE	MAZDA_CAR	1.5L_L4_N																							4,950	5,261	4,765				
FNTE	MAZDA_CAR	1.6L_L4_N													5,458													5,162	5,312	1,962	
FNTE	MAZDA_CAR	1.8L_L4_N																							3,081	3,102	260	6,519	3,822	1,095	496
FNTE	MAZDA_CAR	2.0L_L4_N																							4,544	5,375	5,338	5,613	4,929	3,672	7,316
FNTE	MAZDA_CAR	2.2L_L4_N																11,274	13,010	9,113	2,459										
FNTE	MAZDA_CAR	2.2L_L4_T																	5,448	230											
FNTE	MAZDA_CAR	2.3L_V6_S																						1,155	282	275	325	400	415	113	84
FNTE	MAZDA_CAR	2.5L_V6_N																						3,184	2,162	1,614	2,105	2,115	1,991	635	519
FNTE	MAZDA_CAR	3.0L_V6_N															2,763	2,504		1,436	3,088	670	923	179							
FNTE	MAZDA_TRK	2.2L_L4_N																		5,370											
FNTE	MAZDA_TRK	2.3L_L4_N																							3,020	2,276					
FNTE	MAZDA_TRK	2.5L_L4_N																									2,379	1,974	1,310	157	
FNTE	MAZDA_TRK	2.5L_V6_N																											6,733	1,302	
FNTE	MAZDA_TRK	3.0L_V6_N																5,829		9,624	8,373	6,506	6,627	5,259	852		3,378			485	306
FNTE	MAZDA_TRK	4.0L_V6_N																							495	486	676	366			
FNTE	MERCEDES_CAR	2.8L_L6_N																									2,360	3,862			
FNTE	MERCEDES_CAR	3.2L_V6_N																									8,861				
FNTE	MERCEDES_TRK	3.2L_V6_N																									7,629				
FNTE	MERCURY_CAR	1.9L_L4_N														644				3,783	1,629	4,871	3,781	5,704	1,466						
FNTE	MERCURY_CAR	2.0L_L4_N																								5,422	3,439	1,844			
FNTE	MERCURY_CAR	2.3L_L4_N																				2,781	1,570								
FNTE	MERCURY_CAR	2.3L_L4_T											193	236	165																
FNTE	MERCURY_CAR	2.5L_V6_N																						1,546	603	241	1,222	6,245	3,009	793	445
FNTE	MERCURY_CAR	3.0L_V6_N													4,113	6,038	3,577	3,583	3,348	2,715	2,865	1,322	2,005	2,952	6,958	1,241		2,565	3,926	2,265	2,339
FNTE	MERCURY_CAR	3.8L_V6_N															4,497	9,837	6,683	5,694	7,570	10,777	5,603	2,413	987	676					
FNTE	MERCURY_CAR	4.6L_V8_N																			5,761	3,143	6,102	6,950	5,142	5,466	3,735	4,992	5,340	2,060	1,250
FNTE	MERCURY_TRK	3.0L_V6_N																					6,482	8,575	5,579	5,675	3,004				
FNTE	MERCURY_TRK	3.3L_V6_N																										3,504			
FNTE	MERCURY_TRK	4.0L_V6_N																									1,066	1,032	768	136	1,546
FNTE	MERCURY_TRK	4.6L_V8_N																													738
FNTE	MERCURY_TRK	5.0L_V8_N																									2,532	1,950	2,110	516	
FNTE	MERKUR_CAR	2.3L_L4_T												478	492	469	393	211													
FNTE	MERKUR_CAR	2.9L_V6_N															1,337	416													
FNTE	MITSUBISHI_CAR	1.5L_L4_N																	4,592	3,685	1,122	1,369	3,120	5,063	1,983	3,078	4,050	6,293	1,040	443	300
FNTE	MITSUBISHI_CAR	1.8L_L4_N																	3,300	2,206	3,773				204	1,487	439	357	6,779	3,957	
FNTE	MITSUBISHI_CAR	2.0L_L4_N																	6,257	3,343	3,242	1,559	559	5,928	5,041	6,189	4,954	4,649			
FNTE	MITSUBISHI_CAR	2.0L_L4_T																	1,680	840	492			1,923	1,292	2,749	1,391	937			
FNTE	MITSUBISHI_CAR	2.4L_L4_N													1,737	1,549					1,390	514	5,970	6,689	4,092	4,220	4,234	5,886	12,243	8,082	6,257
FNTE	MITSUBISHI_CAR	3.0L_V6_N															1,166	232	376	911	5,896	1,763	2,322	2,276	532	2,105	1,539	3,141	7,259	4,679	2,163
FNTE	MITSUBISHI_CAR	3.0L_V6_T																		516	655	185	223	239	57	90	54	47			
FNTE	MITSUBISHI_TRK	2.4L_L4_N														1,549	1,611		3,856	3,757	2,642	1,465	2,427	1,620		391					
FNTE	MITSUBISHI_TRK	3.0L_V6_N																								2,839	6,136	4,280	8,754	3,231	1,223
FNTE	MITSUBISHI_TRK	3.5L_V6_N																							544	1,843	1,190	1,441	1,957	3,873	2,669
FNTE	NISSAN_CAR	1.6L_L4_N																		21,364	24,825	24,069	28,931		24,632	24,229	16,235	12,436			
FNTE	NISSAN_CAR	1.8L_L4_N																											8,641	5,858	6,128
FNTE	NISSAN_CAR	1.8L_L4_T											802	412	250																
FNTE	NISSAN_CAR	2.0L_L4_N											6,447	8,128	9,813										1,057		768	625	1,160	1,301	
FNTE	NISSAN_CAR	2.4L_L4_N																						21,033	11,702	23,831	20,350	20,282	15,631	10,001	
FNTE	NISSAN_CAR	2.4L_V6_N											7,203																		
FNTE	NISSAN_CAR	3.0L_V6_N											5,429	17,711			9,387	15,139	27,493	13,271	7,258	8,118	7,533	682	19,367	14,734	10,775	8,273	16,610	4,072	
FNTE	NISSAN_CAR	3.0L_V6_T											2,023	1,229			498							18,885							
FNTE	NISSAN_TRK	2.4L_L4_N																								16,396	12,776	5,168	10,224		
FNTE	NISSAN_TRK	3.0L_V6_N																	5,526	6,852	8,104	7,832	17,688	27,279	11,250	12,388	5,193				
FNTE	NISSAN_TRK	3.3L_V6_N																							6,327	10,963	6,942	13,062	36,417	10,526	6,474
FNTE	OLDSMOBILE_CAR	1.8L_L4_N										233	670	503																	
FNTE	OLDSMOBILE_CAR	2.0L_L4_N												316	246	505	288														
FNTE	OLDSMOBILE_CAR	2.2L_L4_N																					568		383						
FNTE	OLDSMOBILE_CAR	2.4L_L4_N																							547	2,475					
FNTE	OLDSMOBILE_CAR	2.5L_L4_N									1,149	1,483	2,028	4,971	5,969	4,089	1,985	1,951	2,060	1,617											
FNTE	OLDSMOBILE_CAR	2.8L_V6_N													6,633	2,730	5,769	5,414													
FNTE	OLDSMOBILE_CAR	3.0L_V6_N												903	1,483	1,636	669														
FNTE	OLDSMOBILE_CAR	3.1L_V6_N																1,686	4,649	4,240	2,928	2,571	9,120	8,461	7,609	3,561	3,343	1,407			
FNTE	OLDSMOBILE_CAR	3.4L_V6_N																		331	515	439	811	377					2,424	763	565
FNTE	OLDSMOBILE_CAR	3.5L_V6_N																											3,117	1,356	269

Metering_ECS	Make_CarTrk	Engine	MY74	MY75	MY76	MY77	MY78	MY79	MY80	MY81	MY82	MY83	MY84	MY85	MY86	MY87	MY88	MY89	MY90	MY91	MY92	MY93	MY94	MY95	MY96	MY97	MY98	MY99	MY00	MY01	MY02
FNTE	OLDSMOBILE_CAR	3.8L_V6_N												7,874	10,626	14,546	13,738	8,534	5,850	3,946	5,569	2,593	3,866		2,176	2,194	6,509	2,296			
FNTE	OLDSMOBILE_CAR	3.8L_V6_S																			69	44	36	213	97	44	29				
FNTE	OLDSMOBILE_CAR	4.0L_V8_N																							977	1,113	954	542			
FNTE	OLDSMOBILE_TRK	3.1L_V6_N																	2,006	1,465	185										
FNTE	OLDSMOBILE_TRK	3.4L_V6_N																							222	811	1,239	1,211			
FNTE	OLDSMOBILE_TRK	4.3L_V6_N																					819		567	939	933				
FNTE	PLYM/MITS_CAR	1.5L_L4_N																	625	1,252	666	67									
FNTE	PLYM/MITS_CAR	1.8L_L4_N																				362	99								
FNTE	PLYM/MITS_CAR	2.0L_L4_N											263	435	705	697	275														
FNTE	PLYM/MITS_CAR	2.4L_L4_N																				146									
FNTE	PLYM/MITS_CAR	2.6L_L4_T											77	67	121																
FNTE	PLYMOUTH_CAR	2.0L_L4_N																				212		10,322	226	10,474	8,788	5,023	6,261		
FNTE	PLYMOUTH_CAR	2.2L_L4_N															4,232	3,722	1,422	1,209	902	1,202	883								
FNTE	PLYMOUTH_CAR	2.4L_L4_N																								95	2,242	1,394	665		
FNTE	PLYMOUTH_CAR	2.5L_L4_N																	3,170	3,600	2,621	3,008	2,791	344							
FNTE	PLYMOUTH_CAR	3.0L_V6_N																363	2,616	2,231	1,391	1,212	1,269	372							
FNTE	PLYMOUTH_CAR	3.3L_V6_N																		457	380										
FNTE	PLYMOUTH_CAR	3.5L_V6_N																				44						350	278	93	
FNTE	PLYMOUTH_TRK	2.4L_L4_N																										3,244	1,316		
FNTE	PLYMOUTH_TRK	2.5L_L4_N																				993	827	640							
FNTE	PLYMOUTH_TRK	3.0L_V6_N														4,718	9,544	8,682	5,628	2,781	5,285	7,293	7,841	5,647	5,626	984	761				
FNTE	PLYMOUTH_TRK	3.3L_V6_N																							7,420	8,176	7,612	6,129	1,611		
FNTE	PLYMOUTH_TRK	3.8L_V6_N																					1,627	583			99	332			
FNTE	PONTIAC_CAR	1.6L_L4_N																1,722	1,245	1,073	757	218									
FNTE	PONTIAC_CAR	1.8L_L4_N									70	447	1,039	855																	
FNTE	PONTIAC_CAR	2.0L_L4_N														1,064	1,243	2,761	2,663	3,077	1,857	2,046	2,768								
FNTE	PONTIAC_CAR	2.2L_L4_N																							3,037	4,069	3,736				
FNTE	PONTIAC_CAR	2.4L_L4_N																							6,887	6,322	3,488				
FNTE	PONTIAC_CAR	2.5L_L4_N									647	362	3,356	3,395	4,113	5,614	4,434	2,998	2,591	3,443											
FNTE	PONTIAC_CAR	2.8L_V6_N												4,840	6,131	4,199	6,037	6,841													
FNTE	PONTIAC_CAR	3.0L_V6_N												916	865	2,211															
FNTE	PONTIAC_CAR	3.1L_V6_N																1,384	5,176	5,692	4,262	3,146	9,425	11,097	8,165	5,447	4,051	1,887			
FNTE	PONTIAC_CAR	3.4L_V6_N																		254	387	214	255	244					5,181	2,707	1,649
FNTE	PONTIAC_CAR	3.8L_V6_N														2,324	2,220	2,874	2,198	1,297	3,462	2,459	2,834		3,768	8,269	5,928	6,072	4,869	1,939	1,007
FNTE	PONTIAC_CAR	3.8L_V6_S																			658	512	358	312	229	1,745	2,259	1,416	1,777	427	206
FNTE	PONTIAC_TRK	3.1L_V6_N																	2,246	1,182	379	214	137	197							
FNTE	PONTIAC_TRK	3.4L_V6_N																							520	2,567	2,687	2,132			
FNTE	SATURN_CAR	1.9L_L4_N																		5,182	14,579	24,731	27,254	30,969	30,970	32,241	24,629				
FNTE	SUBARU_CAR	1.8L_H4_N															2,081	618				2,235	446	864	138						
FNTE	SUBARU_CAR	2.2L_H4_N																							5,938	3,294	2,441	2,123			
FNTE	SUBARU_CAR	2.5L_H4_N																								3,574	8,957	8,605			
FNTE	SUBARU_CAR	3.0L_V6_N																												338	280
FNTE	SUZUKI_CAR	1.3L_L4_N																924	250	432	445	580	636	401	142						
FNTE	SUZUKI_CAR	1.6L_L4_N																						325	411	818	1,545	604	199		
FNTE	SUZUKI_CAR	1.8L_L4_N																										431	1,193	749	572
FNTE	SUZUKI_TRK	1.3L_L4_N																	238	240	183	57	89								
FNTE	SUZUKI_TRK	1.6L_L4_N																1,864	241	999	875	1,343	1,249	1,754	739	697	382				
FNTE	SUZUKI_TRK	1.8L_L4_N																							532	578	645				
FNTE	SUZUKI_TRK	2.0L_L4_N																										609	491	275	155
FNTE	SUZUKI_TRK	2.5L_V6_N																										1,860	2,708	1,221	544
FNTE	SUZUKI_TRK	2.7L_V6_N																												1,048	1,488
FNTE	TOYOTA_CAR	1.5L_L4_N																	4,908	15,706	26,099	21,131	19,595		12,510						
FNTE	TOYOTA_CAR	1.6L_L4_N												5,384	5,762	5,717	3,596	3,178	36,467	33,194	27,688	30,051		31,201	15,593	26,412					
FNTE	TOYOTA_CAR	1.8L_L4_N																							20,797	12,843					
FNTE	TOYOTA_CAR	2.0L_L4_N										3,464	10,319	15,003	34,276	40,225	43,392	44,515													
FNTE	TOYOTA_CAR	2.0L_L4_T																	26,121	30,995	919	1,211									
FNTE	TOYOTA_CAR	2.2L_L4_N																	8,371	5,458	31,939	34,762	32,160	35,454	44,038	43,507	49,445	51,922	51,264	16,778	
FNTE	TOYOTA_CAR	2.4L_L4_N										9,430	10,486	7,982																	12,694
FNTE	TOYOTA_CAR	2.5L_V6_N															3,441	11,233	12,602	10,465											
FNTE	TOYOTA_CAR	2.6L_L6_N						856	2,007																						
FNTE	TOYOTA_CAR	2.8L_L6_N								3,598	8,050	9,259	9,734	12,488	9,200	5,695	2,272														
FNTE	TOYOTA_CAR	3.0L_L6_N																	4,148	3,758	1,000	671	646	495		122					
FNTE	TOYOTA_CAR	3.0L_V6_N													3,852	7,094	3,634	9,589			12,496	16,969	21,222	25,159	24,461	28,908	29,945	33,354	35,510	5,949	4,616
FNTE	TOYOTA_TRK	2.0L_L4_N											6,017	8,823																	

Metering_ECS	Make_CarTrk	Engine	MY74	MY75	MY76	MY77	MY78	MY79	MY80	MY81	MY82	MY83	MY84	MY85	MY86	MY87	MY88	MY89	MY90	MY91	MY92	MY93	MY94	MY95	MY96	MY97	MY98	MY99	MY00	MY01	MY02
FNTE	TOYOTA_TRK	2.2L_L4_N																3,563							7,438	12,028	10,412	9,226	6,903		
FNTE	TOYOTA_TRK	2.3L_L4_N													53,003																
FNTE	TOYOTA_TRK	2.4L_L4_N																								14,217	26,208	18,357	12,601	5,159	3,754
FNTE	TOYOTA_TRK	2.4L_L4_S																								1,912					
FNTE	TOYOTA_TRK	2.7L_L4_N																						12,462	6,318	7,626	10,468	10,580	10,850	3,191	2,625
FNTE	TOYOTA_TRK	3.4L_V6_N																							24,098	31,416					
FNTE	TOYOTA_TRK	4.5L_L6_N																							2,670	2,843					
FNTE	VOLVO_CAR	2.3L_L4_N																16,197	11,135	6,913											
FNTE	VOLVO_CAR	2.3L_L4_T																	4,148	3,995											
FNTN	ACURA_CAR	1.7L_L4_N																			578	232									
FNTN	ACURA_CAR	1.8L_L4_N																	25,658	11,172	10,197	9,056	19,632	17,765	13,680	10,082	9,605	6,340	6,145	1,585	
FNTN	ACURA_CAR	2.0L_L4_N																													2,643
FNTN	ACURA_CAR	2.5L_L5_N																			4,103	1,795	1,571								
FNTN	ALFAROMEO_CAR	2.0L_L4_N									229	143	392	242	669	113	196	84		363	128	92									
FNTN	ALFAROMEO_CAR	2.5L_V6_N									89	48	109	65	96	412	101	41													
FNTN	ALFAROMEO_CAR	3.0L_V6_N														40	110			641	108	51		52							
FNTN	AUDI_CAR	1.7L_L4_N								183	350	292																			
FNTN	AUDI_CAR	1.8L_L4_N											672			849															
FNTN	AUDI_CAR	1.8L_L4_T																								1,243	1,462	2,402			
FNTN	AUDI_CAR	2.0L_L4_N																	402												
FNTN	AUDI_CAR	2.1L_L5_N								375	549	462	193	2,745	4,059	465	652	517													
FNTN	AUDI_CAR	2.1L_L5_T								85		115		439		1,542	854	565													
FNTN	AUDI_CAR	2.2L_L5_T																	406	643	40	75	43								
FNTN	AUDI_CAR	2.3L_L5_N																	1,437	434											
FNTN	AUDI_CAR	2.8L_V6_N																			843	1,295	671	883				4,552			
FNTN	AUDI_CAR	4.2L_V8_N																								252	203	237			
FNTN	BMW_CAR	1.8L_L4_N								2,721	2,593	3,013	8,115	2,632						3,604	1,826	2,219	2,986	2,172	871	739					
FNTN	BMW_CAR	1.9L_L4_N																							3,613	4,690	3,051				
FNTN	BMW_CAR	2.0L_L4_N							3,011																						
FNTN	BMW_CAR	2.3L_L4_N															475	173	211	42											
FNTN	BMW_CAR	2.5L_L6_N														6,275	4,460	11,798	8,868	5,691	11,935	10,098	11,174	14,255							
FNTN	BMW_CAR	2.7L_L6_N									1,554	1,809	4,125	7,587	13,131	9,664	4,942														
FNTN	BMW_CAR	2.8L_L6_N						1,044	886	622																					
FNTN	BMW_CAR	3.0L_V8_N																					2,106	1,389							
FNTN	BMW_CAR	3.2L_L6_N							588	231	912	2,156	3,480													2,139	2,418	2,424			
FNTN	BMW_CAR	3.4L_L6_N												3,904	3,101	2,378	5,700	4,305	2,119												
FNTN	BMW_CAR	3.5L_L6_N														167	521		1,839	2,119	1,660										
FNTN	BMW_CAR	4.0L_V8_N																				2,514	4,041	6,371	1,313						
FNTN	BMW_CAR	4.4L_V8_N																								7,434	8,250	3,573	4,055	4,152	
FNTN	BMW_CAR	5.0L_V12_N															637	850	782	1,135	321	309		221	318						
FNTN	BMW_CAR	5.4L_V12_N																								215	358	95	142	101	
FNTN	BUICK_CAR	2.3L_L4_N															437	748	217	210	392	318	399	150							
FNTN	BUICK_CAR	3.3L_V6_N																7,442	6,834	6,427	6,831	6,076									
FNTN	BUICK_CAR	3.8L_V6_N																						1,879							
FNTN	CHEVROLET_CAR	1.0L_L3_N																									2,352	2,441	2,983	2,632	
FNTN	CHEVROLET_CAR	1.8L_L4_N																										3,060	2,220	2,020	835
FNTN	CHEVROLET_CAR	2.2L_L4_N																						9,371				11,618	9,505	5,729	7,510
FNTN	CHEVROLET_CAR	2.3L_L4_N																	452	87	31			275							
FNTN	CHEVROLET_CAR	2.4L_L4_N																										4,148	948	372	122
FNTN	CHEVROLET_CAR	3.8L_V6_N																						1,897							
FNTN	CHEVROLET_TRK	4.2L_L6_N																													5,118
FNTN	DODGE_CAR	2.0L_L4_N																											13,150	6,737	5,761
FNTN	DODGE_CAR	8.0L_V10_N																							289		147	177	241	141	107
FNTN	DODGE_TRK	2.4L_L4_N																							1,751	3,429	4,247				
FNTN	DODGE_TRK	2.5L_L4_N																							1,332	831	4,053	1,229	955	426	
FNTN	DODGE_TRK	3.9L_V6_N																							5,923	8,050	8,747	6,618	8,550	3,178	1,630
FNTN	DODGE_TRK	4.7L_V8_N																											11,222	6,472	7,768
FNTN	DODGE_TRK	5.2L_V8_N																							13,131	16,723	26,408	26,819	12,510	5,790	
FNTN	DODGE_TRK	5.9L_V8_N																							13,142	13,420	16,446	23,626	15,110	8,997	3,720
FNTN	FORD_CAR	1.3L_L4_N																1,687	2,210	2,216	1,181	2,397	2,953	6,896							
FNTN	FORD_CAR	1.8L_L4_N																		5,465	1,269	1,463	596	504							
FNTN	FORD_CAR	2.0L_L4_N																						8,005	10,446	5,352	22,908	13,070	22,595	8,951	4,506
FNTN	FORD_CAR	3.8L_V6_S																	4,378	1,270	754										
FNTN	FORD_TRK	2.9L_V6_N															22,616	16,782	12,541	398	267										

Metering_ECS	Make_CarTrk	Engine	MY74	MY75	MY76	MY77	MY78	MY79	MY80	MY81	MY82	MY83	MY84	MY85	MY86	MY87	MY88	MY89	MY90	MY91	MY92	MY93	MY94	MY95	MY96	MY97	MY98	MY99	MY00	MY01	MY02
FNTN	FORD_TRK	3.0L_V6_N													5,310	14,362	15,802	29,612	16,671	16,717	17,634	27,324									
FNTN	FORD_TRK	4.0L_V6_N																	8,687	46,766	48,389	52,420									
FNTN	GMC_TRK	4.2L_L6_N																													2,178
FNTN	HONDA_CAR	1.5L_L4_N												1,531	5,116	5,036	28,646	18,667			25,968	36,163	31,818	44,914							
FNTN	HONDA_CAR	1.6L_L4_N															2,903	4,878	9,091	7,502	3,897	16,186	17,968	24,951	49,256	63,759	72,957	52,695	65,888		
FNTN	HONDA_CAR	2.0L_L4_N																										15,299	15,539	4,382	2,689
FNTN	HONDA_CAR	2.3L_L4_N																			4,550	2,550	1,727	1,649							
FNTN	HONDA_CAR	2.7L_V6_N																						6,360	5,034	4,522					
FNTN	HYUNDAI_CAR	1.5L_L4_N																							3,075	2,339	3,262	3,799	6,308	769	678
FNTN	HYUNDAI_CAR	1.6L_L4_N																												3,306	2,944
FNTN	HYUNDAI_CAR	1.8L_L4_N																							1,941	2,777	2,710				
FNTN	HYUNDAI_CAR	2.0L_L4_N																									1,424	5,337	10,071	4,289	2,790
FNTN	HYUNDAI_CAR	2.5L_V6_N																										1,452	2,528	754	
FNTN	HYUNDAI_CAR	2.7L_V6_N																													1,335
FNTN	HYUNDAI_TRK	2.0L_L4_N																												1,138	1,257
FNTN	INFINITI_CAR	3.0L_V6_N																												2,448	
FNTN	INFINITI_CAR	3.5L_V6_N																												2,280	1,449
FNTN	INFINITI_CAR	4.5L_V8_N																													515
FNTN	JAGUAR_CAR	2.5L_V6_N																													706
FNTN	JAGUAR_CAR	3.0L_V6_N																												1,371	1,607
FNTN	JAGUAR_CAR	3.6L_L6_N																2,851													
FNTN	JAGUAR_CAR	4.0L_V6_N																			963	1,551	2,450								
FNTN	JAGUAR_CAR	4.0L_V8_N																									4,874	3,773	2,665	1,010	286
FNTN	JAGUAR_CAR	4.0L_V8_S																							171	126			670	387	192
FNTN	JEEP_TRK	2.5L_L4_N																		2,925	3,253	3,813	3,803	7,684	540	4,855	2,973	1,691	1,677	546	308
FNTN	JEEP_TRK	3.7L_V6_N																													3,690
FNTN	JEEP_TRK	4.0L_L6_N																													4,077
FNTN	JEEP_TRK	4.0L_V6_N																		15,457	13,693	27,205	21,499		29,610	24,983	26,961	27,779	27,203	10,659	
FNTN	JEEP_TRK	4.7L_V8_N																										9,392	9,317	2,728	1,578
FNTN	JEEP_TRK	5.2L_V8_N																							11,760	8,487	6,421				
FNTN	JEEP_TRK	5.9L_V8_N																									1,846				
FNTN	KIA_CAR	1.5L_L4_N																												5,157	3,728
FNTN	KIA_CAR	1.8L_L4_N																									3,313	4,090	8,486	3,000	
FNTN	KIA_CAR	2.4L_L4_N																												1,004	550
FNTN	KIA_CAR	2.5L_V6_N																												280	
FNTN	KIA_CAR	2.7L_V6_N																													834
FNTN	KIA_CAR	3.5L_V6_N																													3,948
FNTN	LANDROVER_TRK	3.5L_V8_N														325	666														
FNTN	LANDROVER_TRK	3.9L_V8_N																810	982	786	704	295	1,273	2,320							
FNTN	LANDROVER_TRK	4.0L_V8_N																							4,333	3,405	3,280	3,398			
FNTN	LANDROVER_TRK	4.6L_V8_N																							430	697	870	986			
FNTN	LEXUS_CAR	3.0L_L6_N																									4,349	5,978	5,057	7,332	2,814
FNTN	LEXUS_CAR	3.0L_V6_N																											23,221	2,276	2,255
FNTN	LEXUS_CAR	4.0L_V8_N																									8,035	5,496	3,373		
FNTN	LEXUS_CAR	4.3L_V8_N																												3,069	2,868
FNTN	LEXUS_CAR	4.7L_V8_N																										2,524	2,797		
FNTN	LEXUS_TRK	3.0L_V6_N																												5,734	2,279
FNTN	LEXUS_TRK	4.7L_V8_N																												725	327
FNTN	MAZDA_CAR	1.3L_ROT_N																1,382		1,427											
FNTN	MAZDA_CAR	1.3L_ROT_T																				1,825	637	160							
FNTN	MAZDA_CAR	1.5L_L4_N																						5,993							
FNTN	MAZDA_CAR	1.6L_L4_N															8,482	8,208	8,298	9,131	8,950	7,172	2,312	697							
FNTN	MAZDA_CAR	1.8L_L4_N																	2,073	5,664	5,785	6,041	11,629	3,481							
FNTN	MAZDA_CAR	1.8L_V6_N																			1,432	828	246								
FNTN	MAZDA_CAR	2.0L_L4_N																				6,448	4,385	6,393							
FNTN	MAZDA_CAR	2.5L_V6_N																				5,755	3,813	2,660							
FNTN	MAZDA_TRK	2.3L_L4_N																												133	246
FNTN	MAZDA_TRK	3.0L_V6_N																							3,917	3,423					526
FNTN	MAZDA_TRK	4.0L_V6_N																											190	96	78
FNTN	MERCEDES_CAR	2.2L_L4_N																						3,242							
FNTN	MERCEDES_CAR	2.3L_L4_N											2,833	4,546	3,713	3,634	3,029			2,363	1,387	1,721					9,430	8,177	5,533		
FNTN	MERCEDES_CAR	2.6L_L6_N														2,229	1,754	4,999													
FNTN	MERCEDES_CAR	2.8L_L6_N																				1,740		4,083					1,583		
FNTN	MERCEDES_CAR	3.0L_L6_N													5,263	4,551	6,314	8,284													

Metering_ECS	Make_CarTrk	Engine	MY74	MY75	MY76	MY77	MY78	MY79	MY80	MY81	MY82	MY83	MY84	MY85	MY86	MY87	MY88	MY89	MY90	MY91	MY92	MY93	MY94	MY95	MY96	MY97	MY98	MY99	MY00	MY01	MY02
FNTN	MERCEDES_CAR	3.0L_L6_T															689	644													
FNTN	MERCEDES_CAR	3.2L_L6_N																			864	3,109	1,156	2,844							
FNTN	MERCEDES_CAR	4.2L_V8_N																			1,499	881					775	674			
FNTN	MERCEDES_CAR	4.3L_V8_N																									1,247	3,666			
FNTN	MERCEDES_CAR	5.0L_V8_N																			1,383	1,534	2,002	3,133				2,101			
FNTN	MERCEDES_CAR	5.5L_V8_N																										249	299	952	640
FNTN	MERCEDES_CAR	6.0L_V12_N																			247	189	145	387							
FNTN	MERCEDES_CAR	6.0L_V8_N																				152	264	227							
FNTN	MERCEDES_TRK	4.3L_V8_N																										3,370	2,643	735	
FNTN	MERCEDES_TRK	5.0L_V8_N																													347
FNTN	MERCEDES_TRK	5.5L_V8_N																											418	215	66
FNTN	MERCURY_CAR	1.6L_L4_N															3,897	3,607		2,386	495	655	265								
FNTN	MERCURY_CAR	1.6L_L4_T																		944	104	81	44								
FNTN	MERCURY_CAR	1.8L_L4_N																		789	119	614	200	94							
FNTN	MERCURY_CAR	2.0L_L4_N																						2,421	3,076	1,308	2,527	2,328	1,206		
FNTN	MERCURY_CAR	3.8L_V6_S																	350												
FNTN	MERCURY_TRK	3.0L_V6_N																				9,723									
FNTN	MERCURY_TRK	3.3L_V6_N																											2,025	470	256
FNTN	MITSUBISHI_TRK	2.4L_L4_N																									1,091	352			
FNTN	MITSUBISHI_TRK	3.0L_V6_N																							1,431						
FNTN	NISSAN_CAR	2.5L_L4_N																													7,768
FNTN	NISSAN_CAR	3.5L_V6_N																													4,789
FNTN	OLDSMOBILE_CAR	2.2L_L4_N																						278							464
FNTN	OLDSMOBILE_CAR	2.3L_L4_N															1,796	2,373	1,136	1,394	2,685	1,311	1,278	580							
FNTN	OLDSMOBILE_CAR	2.4L_L4_N																										2,163	2,510	1,440	
FNTN	OLDSMOBILE_CAR	3.3L_V6_N																7,181	5,162	4,421	5,195	6,394									
FNTN	OLDSMOBILE_CAR	3.8L_V6_N																						3,208							
FNTN	PEUGEOT_CAR	1.9L_L4_N																528		105											
FNTN	PEUGEOT_CAR	2.1L_L4_T																	22	73											
FNTN	PEUGEOT_CAR	2.2L_L4_N									95	340	767	813	625	520	295	144													
FNTN	PLYMOUTH_CAR	2.0L_L4_N																												2,422	
FNTN	PLYMOUTH_TRK	2.4L_L4_N																							983	2,226	2,742				
FNTN	PONTIAC_CAR	2.2L_L4_N																						1,420				3,327	2,629	1,895	2,846
FNTN	PONTIAC_CAR	2.3L_L4_N															1,595	3,442	2,258	1,988	4,243	3,910	4,502	5,057							
FNTN	PONTIAC_CAR	2.4L_L4_N																										5,096	4,219	2,480	
FNTN	PONTIAC_CAR	3.3L_V6_N																			2,802	3,763									
FNTN	PONTIAC_CAR	3.8L_V6_N																						3,352							
FNTN	PORSCHE_CAR	2.5L_L4_N												1,533	1,044	1,044	392	278													
FNTN	PORSCHE_CAR	2.5L_L4_T													677	272	149	131													
FNTN	PORSCHE_CAR	3.0L_L4_N																	294	144		128	236	92							
FNTN	PORSCHE_CAR	3.2L_H6_N												1,046	1,332		1,233	977													
FNTN	PORSCHE_CAR	3.3L_H6_T																		78	180										
FNTN	PORSCHE_CAR	3.3L_L6_T													235	251	165	174													
FNTN	PORSCHE_CAR	3.6L_H6_N																	1,006	970	380	300	230	1,905							
FNTN	PORSCHE_CAR	3.6L_H6_T																					71		361						
FNTN	PORSCHE_CAR	5.0L_V8_N														977	410	209													
FNTN	SAAB_CAR	2.0L_L4_N										731		1,001	1,456	1,535	1,314	1,147	697												
FNTN	SAAB_CAR	2.0L_L4_T												957	525	1,434	1,884	1,437			516	315	357	519	962	1,226	733	3,113	1,509	960	512
FNTN	SAAB_CAR	2.1L_L4_N																		990	1,005	684	178								
FNTN	SAAB_CAR	2.3L_L4_N																	151	353	403	320	676	1,337							
FNTN	SAAB_CAR	2.3L_L4_T																		307	270	332	276	211			74	1,446	863	779	276
FNTN	SAAB_CAR	2.5L_V6_N																					502	908							
FNTN	SAAB_CAR	3.0L_V6_T																										418	451	515	47
FNTN	SATURN_CAR	2.2L_L4_N																											5,214	2,234	
FNTN	SATURN_CAR	3.0L_V6_N																											4,752	1,296	620
FNTN	SUBARU_CAR	1.8L_H4_N																	827	1,129	1,403	789	153								
FNTN	SUBARU_CAR	2.0L_L4_T																													1,921
FNTN	SUBARU_CAR	2.2L_H4_N																	5,479	3,531	2,836	2,898	610	4,164					931		
FNTN	SUBARU_CAR	2.5L_H4_N																											9,162	3,627	2,330
FNTN	SUBARU_CAR	2.7L_H6_N															323	268		35											
FNTN	SUBARU_CAR	3.3L_H6_N																			798	37	196	128							
FNTN	TOYOTA_CAR	1.5L_L4_N																								9,131	317		8,662	3,014	1,334
FNTN	TOYOTA_CAR	1.8L_L4_N																									41,545	44,964	45,729	22,794	11,060
FNTN	TOYOTA_TRK	2.0L_L4_N																												4,449	3,291

Metering_ECS	Make_CarTrk	Engine	MY74	MY75	MY76	MY77	MY78	MY79	MY80	MY81	MY82	MY83	MY84	MY85	MY86	MY87	MY88	MY89	MY90	MY91	MY92	MY93	MY94	MY95	MY96	MY97	MY98	MY99	MY00	MY01	MY02
FNTN	TOYOTA_TRK	3.0L_V6_N	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	17,309	14,336	26,768	7,273	5,117
FNTN	TOYOTA_TRK	3.4L_V6_N	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	29,704	32,963	31,765	13,265	10,140
FNTN	TOYOTA_TRK	4.7L_V8_N	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	1,858	3,351	8,896	8,893	7,451
FNTN	VOLVO_CAR	1.9L_L4_T	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	5,363	2,803	814
FNTN	VOLVO_CAR	2.1L_L4_N	.	.	.	1,258	2,008	2,890	3,884	4,552	4,701	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
FNTN	VOLVO_CAR	2.1L_L4_T	.	.	.	.	.	.	.	244	1,170	1,488	1,249	420	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
FNTN	VOLVO_CAR	2.3L_L4_N	.	.	.	.	.	.	.	.	.	6,978	10,760	12,444	17,491	16,476	14,078	.	.	.	.	.	.	.	.	.	.	.	.	.	.
FNTN	VOLVO_CAR	2.3L_L5_T	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	3,385	1,438	3,497	593	483	1,561	335
FNTN	VOLVO_CAR	2.4L_L5_N	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	3,133	.	.	.	7,651	4,654	.	154	.
FNTN	VOLVO_CAR	2.4L_L5_T	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	6,126	4,299	7,964	4,141	1,930
FNTN	VOLVO_CAR	2.7L_V6_N	.	.	.	.	335	609	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
FNTN	VOLVO_CAR	2.8L_V6_N	.	.	.	.	.	.	426	216	140	427	292	181	160	476	389	328	243	.	.	.	.	.	.	.	.	.	.	.	.
FNTN	VW_CAR	1.6L_L4_N	.	.	.	.	.	.	2,097	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
FNTN	VW_CAR	1.8L_L4_N	.	.	.	.	.	.	.	2,372	3,165	2,773	7,752	11,658	14,912	17,224	15,420	14,374	15,028	10,024	9,133	2,186	8,247	16,191	.	.	.	.	.	.	.
FNTN	VW_CAR	1.8L_L4_S	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	331	456	.	319	.	.	.	.	.	.	.
FNTN	VW_CAR	2.0L_L4_N	.	.	.	.	.	.	1,135	.	.	.	.	.	.	.	.	.	589	645	420	4,596	726	2,489	.	.	.	.	26,020	2,614	478
FNTN	VW_CAR	2.2L_L5_N	.	.	.	.	.	.	.	.	316	149	460	527	446	314	119	.	.	.	.	.	.	.	.	.	.	.	.	.	.
FNTN	VW_CAR	2.8L_V6_N	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	110	.	.	.	.	4,738	.	.	.
FNTN	VW_TRK	1.8L_L4_N	.	.	.	.	.	.	.	464	185	42	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
FNTN	VW_TRK	2.0L_L4_N	.	.	.	.	.	.	.	1,232	1,368	1,248	3,397	3,458	2,834	3,199	946	1,165	.	.	.	.	.	.	.	.	.	.	.	.	.

Appendix K

Preparation of Modeling Data

The ASM failure probability models built in this study were based on data obtained from the California historical VID and from the California RSD pilot dataset. The following four subsections describe the SAS computer programs and the datasets that were used and how they were prepared to create the dataset that was used for model building.

General use of the ASM test for emissions inspection in the California I/M program began in about July 1998. In the first two years following this date, vehicles that had been participating in the previous I/M program, which was based on two-speed-idle testing, generally had two-speed-idle tests as their previous-cycle inspection. After about July 2000 almost all vehicles that received ASM emissions tests had ASM tests as their previous-cycle emissions test. One important exception is for those areas of California that were later converted from basic (that is, two-speed idle) to enhanced (that is, ASM) I/M areas. An important example of this is the conversion of the Bay area from basic to enhanced testing in June 2002. This single event added approximately three million vehicles to the California vehicles that received ASM emission tests in the I/M program. Even today, now and then, new areas are converted from the basic to the enhanced I/M program. To be able to calculate ASM failure probabilities using as large a dataset as possible and to be able to calculate ASM failure probabilities for vehicles that had two-speed-idle previous-cycle inspections as well as ASM previous-cycle inspections, we needed to create a modeling dataset that had all of the ASM emissions test results from July 1998 to April 2005 from the BAR-97 dataset. In addition, we needed to obtain data from the period starting approximately two years before July 1998 so that we would have the previous-cycle inspection results, which were based on two-speed-idle testing, for the vehicles that received ASM tests from July 1998 to approximately July 2000. Without this earlier BAR-90 data, ASM tests from July 1998 to approximately July 2000 would be essentially useless for modeling purposes.

VID BAR-90 Data – All of the VID data and SAS programs for preparing it were located in /bigrig/DecisionModel/ASMFprob2005. Staff at the California Bureau of Automotive Repair provided ERG with historical files with BAR-90 data from approximately January 1996 through December 1998. We selected the BAR-90 data from July 1996 through December 1998 to be used in the study because of its consistent data format. The SAS program rdbar90_unix.sas was used to read in the BAR-90 data from BAR90_jul96dec98.sas7bdat. The file contained 21,895,808 records. The program also read in the SAS dataset pass4vinscats.sas7bdat which is the file of all unique, VIN-decodable VINs that were found in the BAR-97 dataset and that were in one of the eight Metering_ECS categories to be modeled. This dataset contained all of the VINs for which ASM failure probability models would be built. The records in the BAR-97 dataset that had been read in and the VINs from pass4vinscats.sas7bdat were merged by VIN to arrive at the intersection of the two files. This intersection had 13,902,902 records with two-speed-idle information from the BAR-90 data that were previous-cycle inspection records for VINs in the BAR-97 data ASM results.

VID BAR-97 Data – Eight programs named makeasmfprobmodelsets_b90_****.sas were used to read in the VID BAR-90 data prepared above and the BAR-97 VID data. Each one of the SAS programs corresponded to the eight categories of Metering_ECS. First, the program read in the BAR-97 VID data with ERG VIN Decoder decodes from VID_data.csv. This file contained 68,985,218 records and covered the period from July 1998 to April 2005. This dataset was merged with pass4vinscats.sas7bdat which contained the list of unique, VIN-decodable VINs that fell in the eight Metering_ECS categories to be modeled. The intersection of these two datasets produced 66,798,483 records for the eight major Metering_ECS categories. This is 96.8% of the observations in the BAR-97 VID.

Preparing VID Data for Fprob Modeling – At this point, the makeasmfprobmodelsets_b90_****.sas programs combined the BAR-90 dataset and the BAR-97 dataset into one large dataset for each of the Metering_ECS categories. Observations, for which the overall emissions result or the overall result was Abort, or for which the test cycle was Missing or were duplicate records, were deleted from the dataset. Observations for any VINs that had valid RSD readings in the RSD pilot dataset were then deleted to keep the ASM failure probability models that would be developed on this dataset independent of the RSD pilot data.

For each VIN, the beginning of an I/M cycle was defined as the first inspection after a previous certification, and the end of an I/M cycle was defined as the next inspection certification. Any VIN that had an I/M cycle with both an ASM and a TSI test was eliminated from the dataset to ensure that inspection results within an I/M cycle were on the same test-cycle basis for the entire dataset. For each VIN, the program then created flags for I/M cycle identification, initial and final test within each I/M cycle, and calculated the time lags between each test within each I/M cycle.

The program then used several VID dataset variables to determine if a repair was made within each I/M cycle. The basic concept is if a vehicle initially passed the inspection and was certified, no repair was made. If a vehicle failed the initial test and was later certified with a pass, the vehicle had been repaired. In the case of repairs, the program assigned a repair date to the date of the certification where the vehicle passed. There were also many combinations of other pass and fail results and the program included special code to assign repair dates.

Since the California VID does not contain the cutpoints that were used for each inspection, the program calculated the cutpoints from the date of the inspection, the emission standards category assigned to the vehicle, and the weight of the vehicle as recorded on the inspection observation record using the A and B coefficients from the cutpoint look-up table. The cutpoint look-up table included cutpoint Phases 1.4 which began on October 4, 1999 through cutpoint Phase 4.3 which began on January 8, 2003. The pass/fail results, which we obtained from our ASM cutpoint look-up table, agree with the pass/fail results in the BAR-97 VID 99.97% of the time. We had to develop the cutpoint code for looking up cutpoints because the VID contains the pass/fail results by ASM mode and we needed to have pass/fail results by ASM mode/pollutant in order to do ASM failure probability modeling on each ASM mode/pollutant.

At this point, we retained only those observations and fields that were necessary to build the ASM failure probability models.

Pilot RSD Data – The RSD pilot data was collected in the period from March 15, 2004 through January 24, 2005. The first program to prepare the pilot program RSD data was mkmasterfile.sas. This program first read in /bigrig/ca_rsd_pilot/from_millhouse/rsd_vin.csv which contained 2,231,515 records. The program also reads in /bigrig/ca_rsd_pilot/from_millhouse/SITES_REV03.csv which contains the grade of the RSD sites. These two files were merged and the VSP was calculated.

In addition, the program converted the RSD hydrocarbon readings to ppm propane which is the standard unit used by RSD researchers. The raw RSD hydrocarbon readings were given to us by ESP as ppm hexane. The conversion equation used was: RSD ppm propane = RSD ppm hexane/0.5116. The RSD data that was saved with other pilot project data in a dataset called mastertests.sas7bdat.

The second program that handled RSD data in preparation for modeling was /bigrig/ca_rsd_pilot/QC_field_data/QCmasterfile.sas. This program read in mastertests.sas7bdat. This program flagged RSD records that had all valid gas measurement flags, had VIN-decodable VINs in the DMV database, were in one of the eight major Metering_ECS categories to be modeled, and had VSPs calculated at the time of the RSD measurement between 5 and 25 kW/Mg. Table K-1 shows how the number of observations decreased as additional data requirements were imposed on the dataset. The final dataset is used in this study to build the models that predict the failure probability of the 69,629 initial-cycle I/M-station ASM inspections that occurred after the pilot RSD measurements.

Table K-1. Selection of Data Records for Models that Use RSD as Inputs

Cumulative Attributes	Number of Records
All RSD records	2,231,515
+ Valid RSD measurements	1,456,274
+ Moderate engine load (5 ≤ VSP ≤ 25 kW/Mg)	843,867
+ No duplicate RSD records	827,487
+ Non-Error VIN decodes	486,286
+ Initial-cycle natural ASM after the RSD	90,574
+ I/M cycle before RSD has been completed	76,982
+ Record produces output from all Fprob models	69,629

Appendix L

Sierra Research ASM/FTP Conversion Equations[44]

[44] "Technical Support Document" for Evaluation of the California Enhanced Vehicle Inspection and Maintenance (Smog Check) Program, April 2004, Draft Report to the Inspection and Maintenance Review Committee, June 2004.

Sierra Research developed revised correlation equations that predict FTP scores from ASM results. We believe that the general methodology followed that developed for the July 2000 evaluation of the Smog Check Program.[45] One difference, however, is that two sets of equations were developed for the current effort – one based on pre-1990 model year vehicles and the other based on 1990 and newer model year vehicles. The correlation equations are provided below.

<u>Pre-1990 Model Year Correlation Equations</u>

$$
\begin{aligned}
\text{FTP\_HC} = 1.2648 * \exp(&- 4.67052 \\
&+ 0.46382 * \text{hc\_term} \\
&+ 0.09452 * \text{co\_term} \\
&+ 0.03577 * \text{nx\_term} \\
&+ 0.57829 * \text{wt\_term} \\
&- 0.06326 * \text{my\_term} \\
&+ 0.20932 * \text{trk})
\end{aligned}
$$

$$
\begin{aligned}
\text{FTP\_CO} = 1.2281 * \exp(&- 2.65939 \\
&+ 0.08030 * \text{hc\_term} \\
&+ 0.32408 * \text{co\_term} \\
&+ 0.03324 * \text{co\_term**2} \\
&+ 0.05589 * \text{nx\_term} \\
&+ 0.61969 * \text{wt\_term} \\
&- 0.05339 * \text{my\_term} \\
&+ 0.31869 * \text{trk})
\end{aligned}
$$

$$
\begin{aligned}
\text{FTP\_NX} = 1.0810 * \exp(&- 5.73623 \\
&+ 0.06145 * \text{hc\_term} \\
&- 0.02089 * \text{co\_term**2} \\
&+ 0.44703 * \text{nx\_term} \\
&+ 0.04710 * \text{nx\_term**2} \\
&+ 0.72928 * \text{wt\_term} \\
&- 0.02559 * \text{my\_term} \\
&- 0.00109 * \text{my\_term**2} \\
&+ 0.10580 * \text{trk})
\end{aligned}
$$

---

[45] T.H. DeFries, C.F. Palacios, S. Kishan, and H.J. Williamson, "Models for Estimating California Fleet FTP Emissions from ASM Measurements," prepared for California Bureau of Automotive Repair, BAR-991225, Eastern Research Group, Inc., Austin, Texas, December 25, 1999.

where:

```
hc_term  =  ln (  (ASM5015_HC*ASM2525_HC) ^ 0.5 )   -   3.72989
co_term  =  ln (  (ASM5015_CO*ASM2525_CO) ^ 0.5 )   +   2.07246
nx_term  =  ln (  (ASM5015_NX*ASM2525_NX) ^ 0.5 )   -   5.83534

my_term  =  model_year   -   1982.71

wt_term  =  ln (vehicle_weight )

trk      =  1   if a light-duty truck
trk      =  0   if a passenger car
```

<u>1990 and Newer Model Year Correlation Equations</u>

```
FTP_HC  =  1.1754  *  exp (  -  6.32723
                             +  0.24549  *  hc_term
                             +  0.09376  *  hc_term**2
                             +  0.06653  *  nx_term
                             +  0.01206  *  nx_term**2
                             +  0.56581  *  wt_term
                             -  0.10438  *  my_term
                             -  0.00564  *  my_term**2
                             +  0.24477  *  trk);

FTP_CO  =  1.2055  *  exp (     0.90704
                             +  0.04418  *  hc_term**2
                             +  0.17796  *  co_term
                             +  0.08789  *  nx_term
                             +  0.01483  *  nx_term**2
                             -  0.12753  *  my_term
                             -  0.00681  *  my_term**2
                             +  0.37580  *  trk);

FTP_NX  =  1.1056  *  exp (  -  6.51660
                             +  0.25586  *  nx_term
                             +  0.04326  *  nx_term**2
                             +  0.65599  *  wt_term
                             -  0.09092  *  my_term
                             -  0.00998  *  my_term**2
                             +  0.24958  *  trk)
```

where:

$$hc\_term = \ln\left((ASM5015\_HC * ASM2525\_HC)^{0.5} \right) - 2.32393$$
$$co\_term = \ln\left((ASM5015\_CO * ASM2525\_CO)^{0.5} \right) + 3.45963$$
$$nx\_term = \ln\left((ASM5015\_NX * ASM2525\_NX)^{0.5} \right) - 3.71310$$

$$my\_term = model\_year - 1993.69$$

$$wt\_term = \ln(vehicle\_weight)$$

trk = 1 if a light-duty truck
trk = 0 if a passenger car

For cases in which the HC or NX ASM scores are zero, they are set to 1 ppm; for cases in which the CO ASM score is zero, it is set to 0.01%.

Appendix M

Demonstration of Data Fit for Model C for ASM2525 NX Unconditional for 1986-2002 FNTE Ford_Car 3.0L_V6_N

Figure M-1.

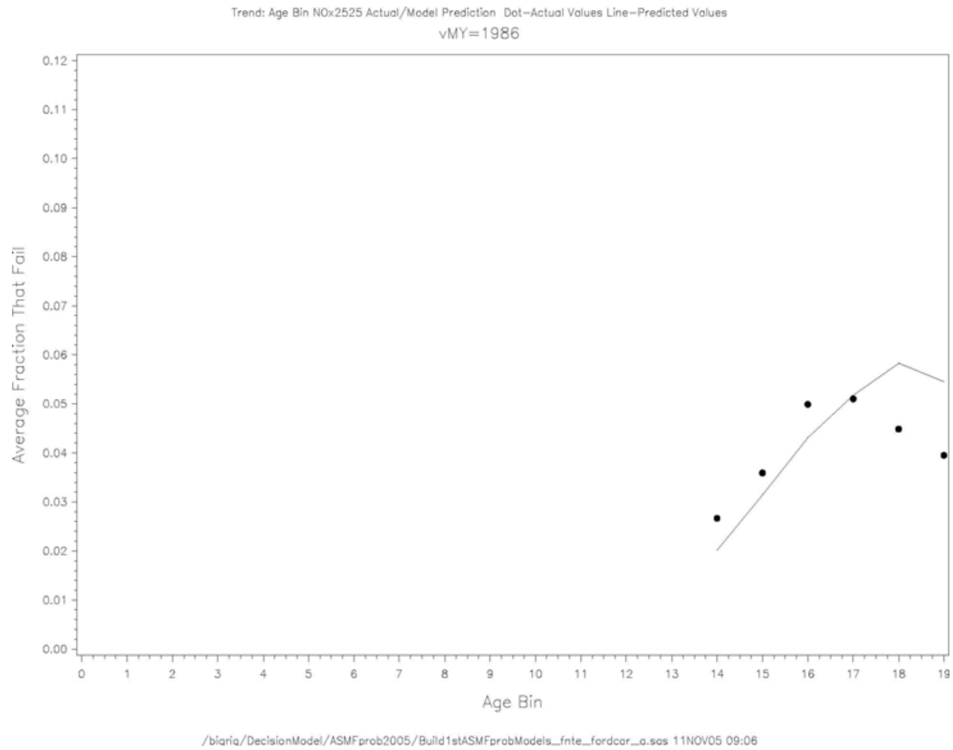


Figure M-2.

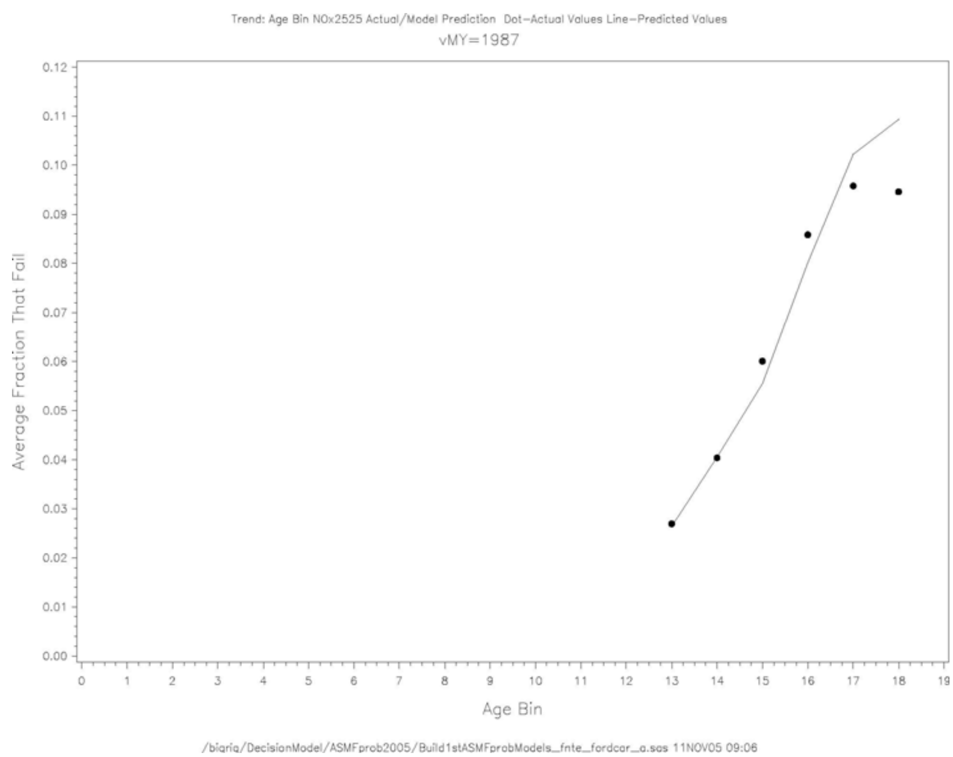


Figure M-3.

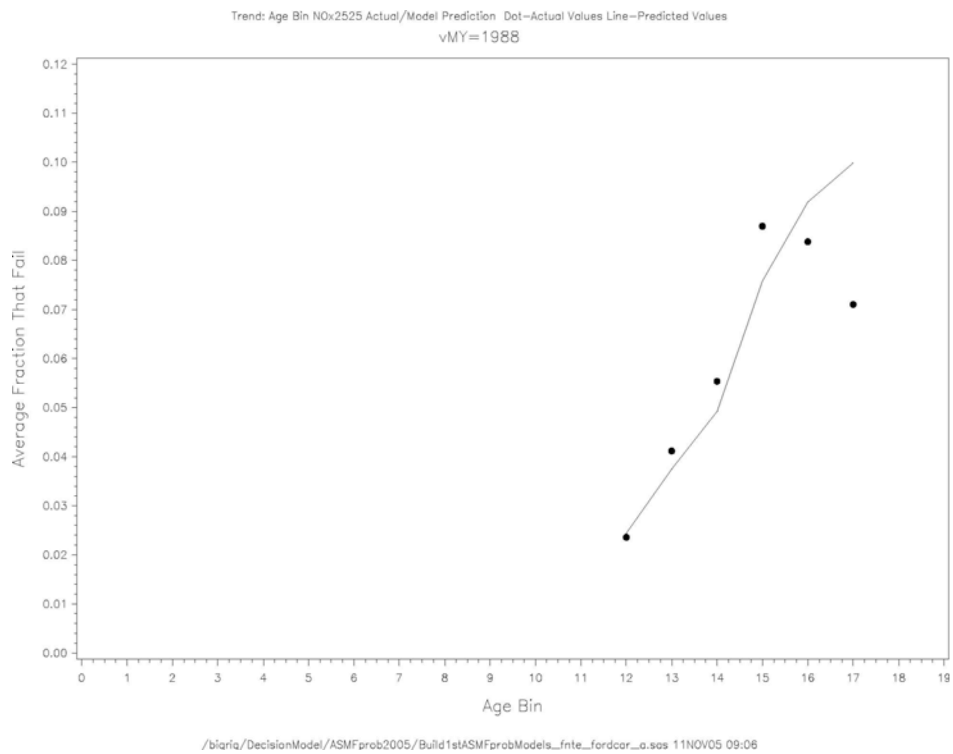


Figure M-4

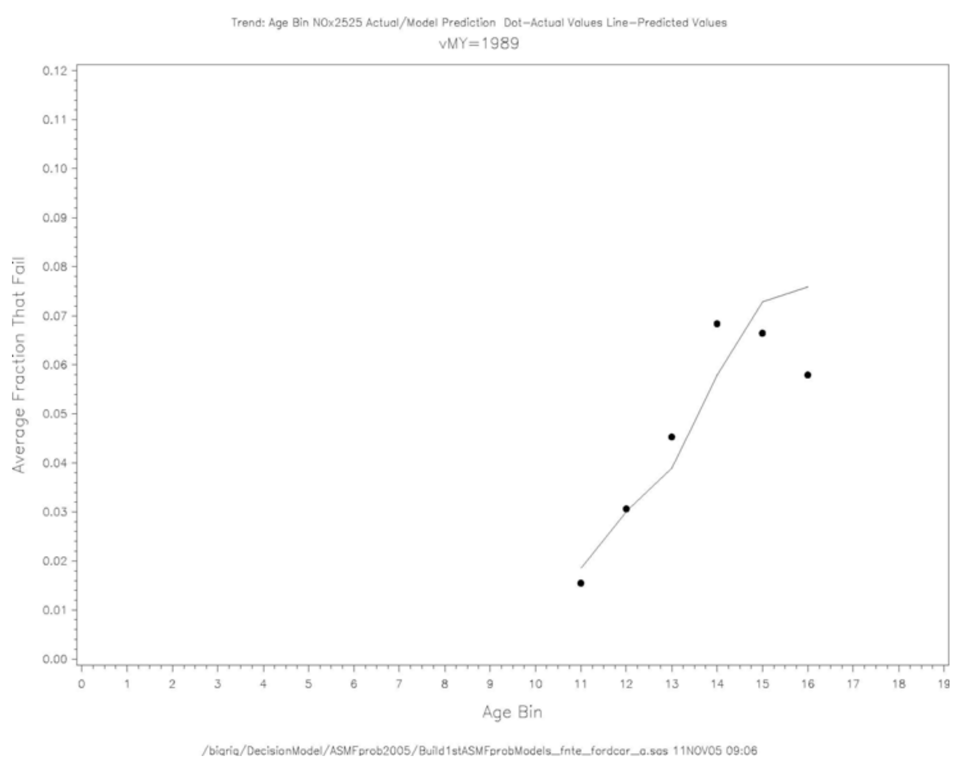


Figure M-5.

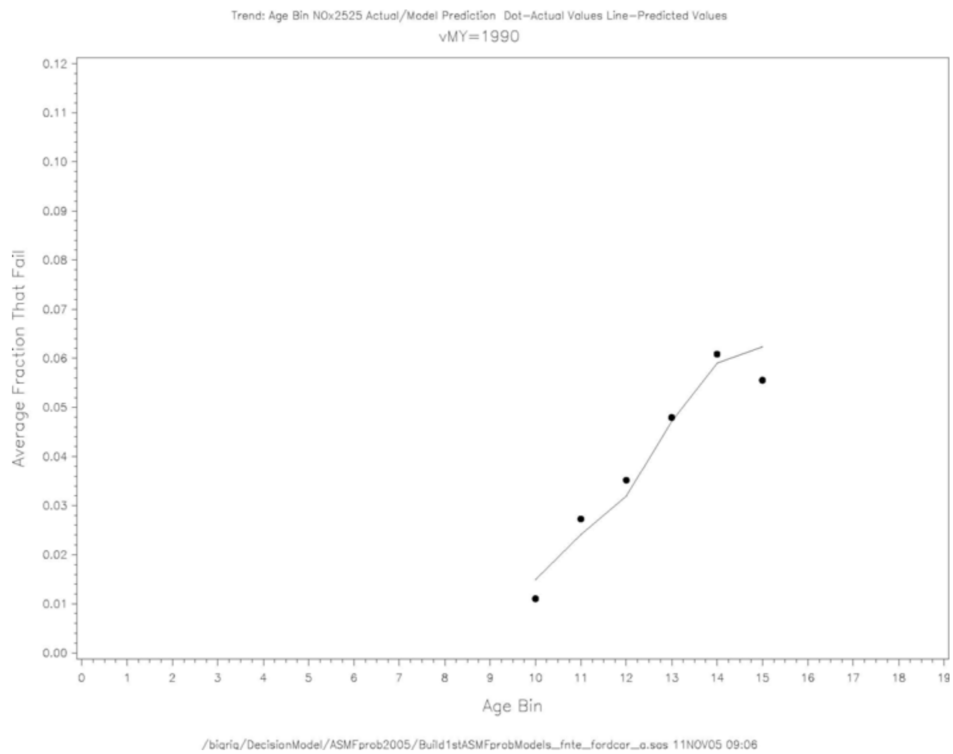


Figure M-6.

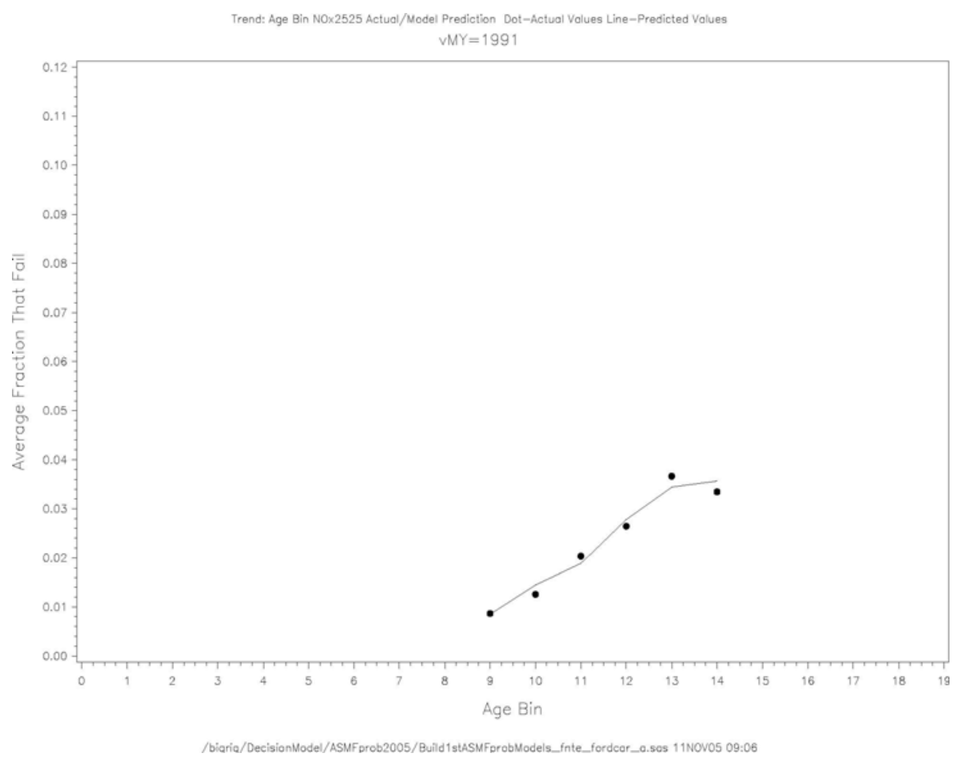


Figure M-7.

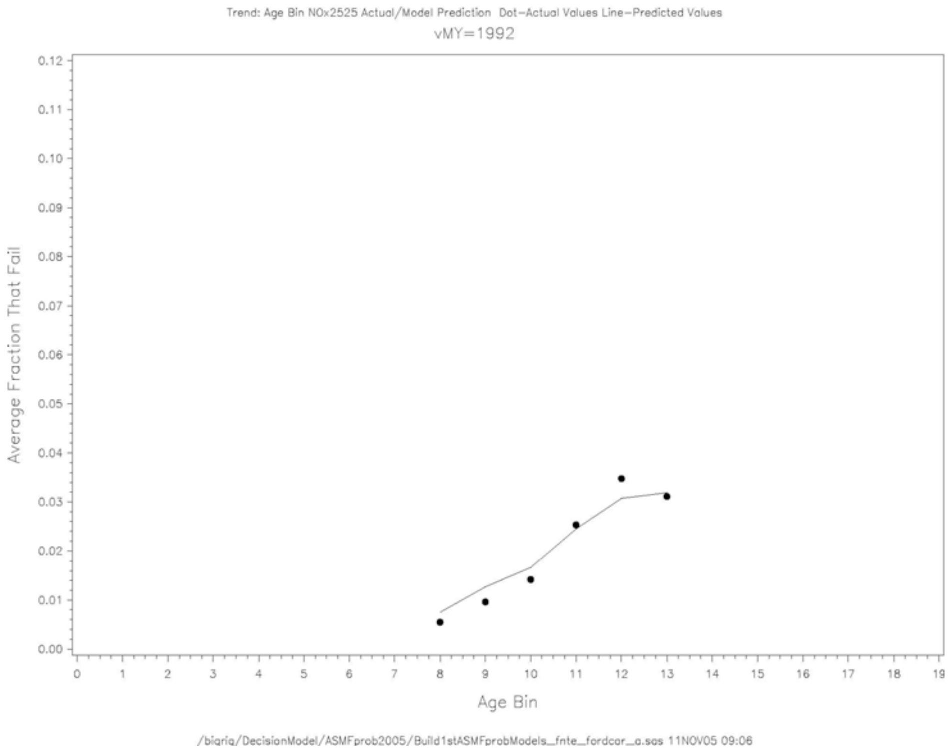


Figure M-8.

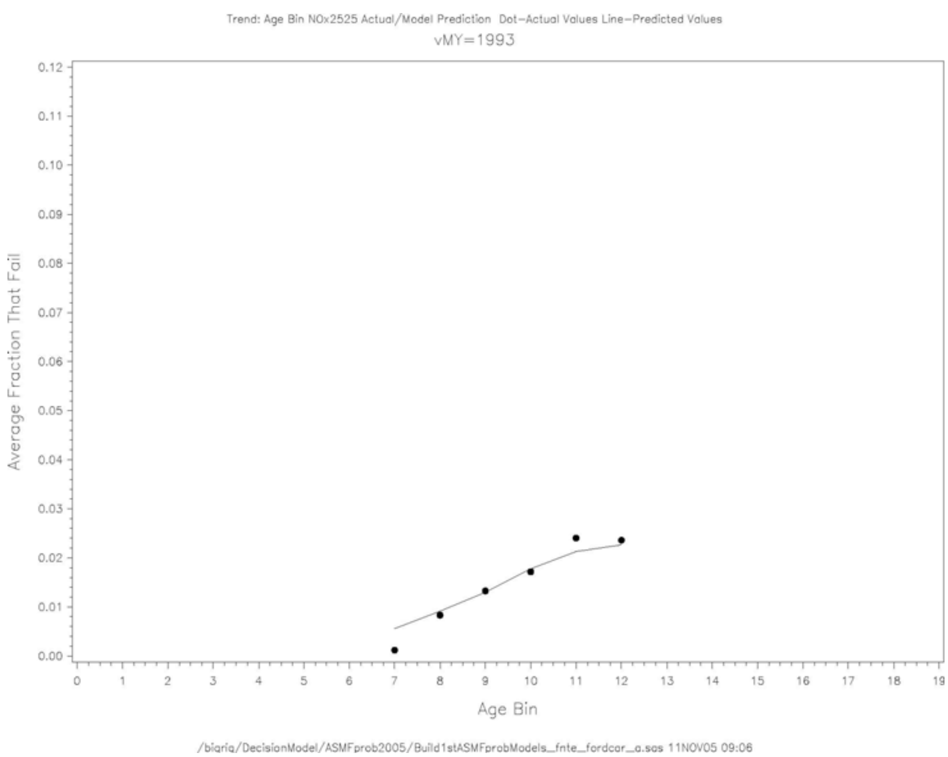


Figure M-9.

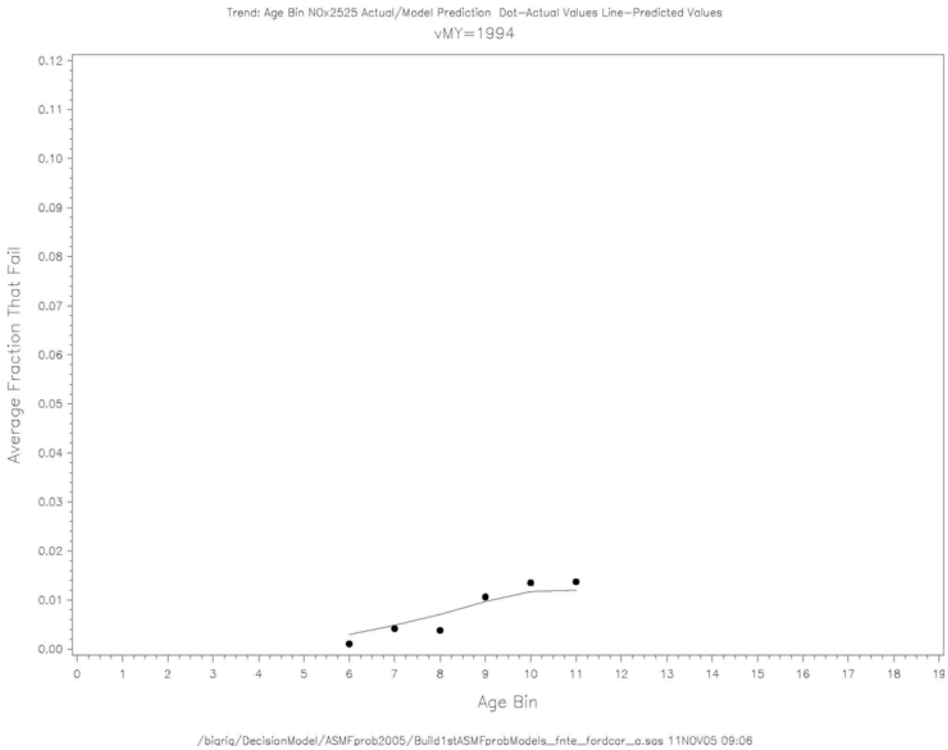


Figure M-10.

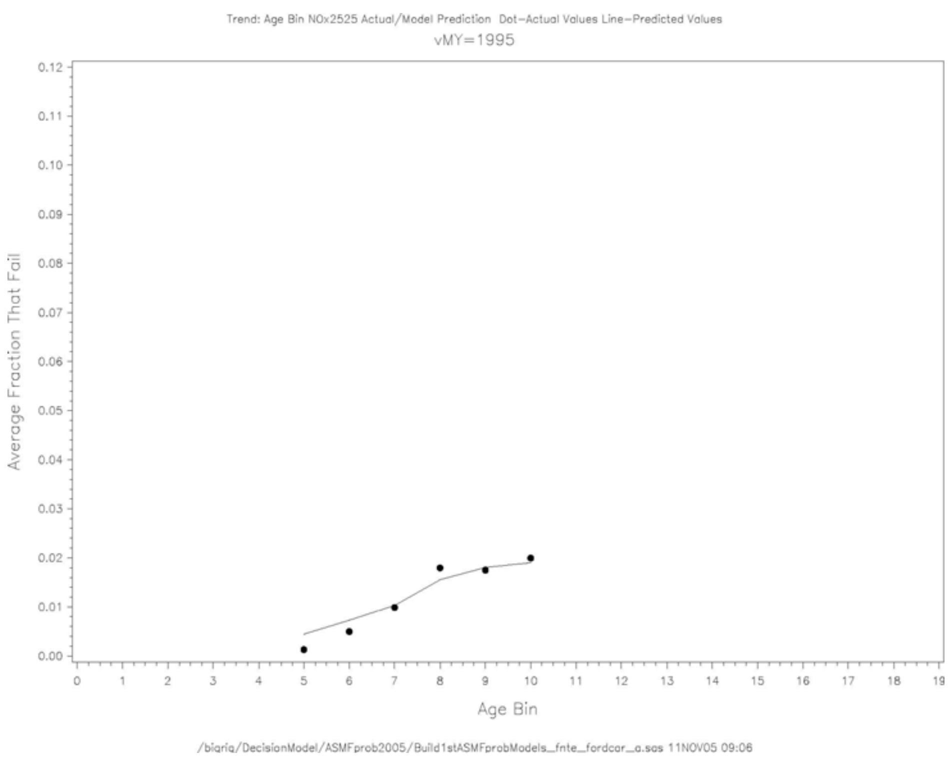


Figure M-11.

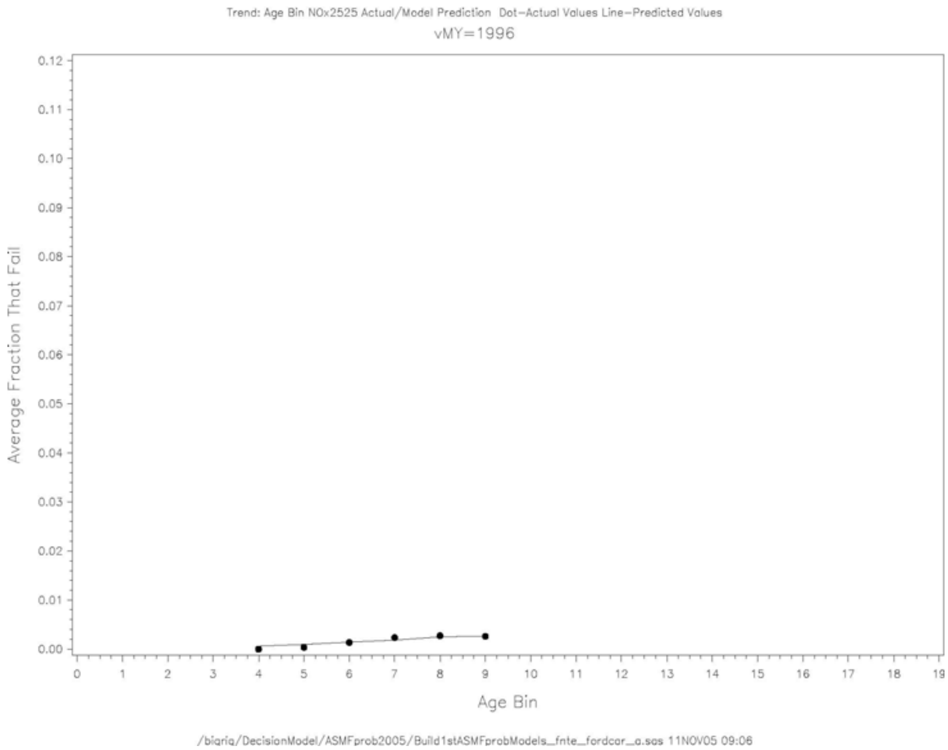


Figure M-12.

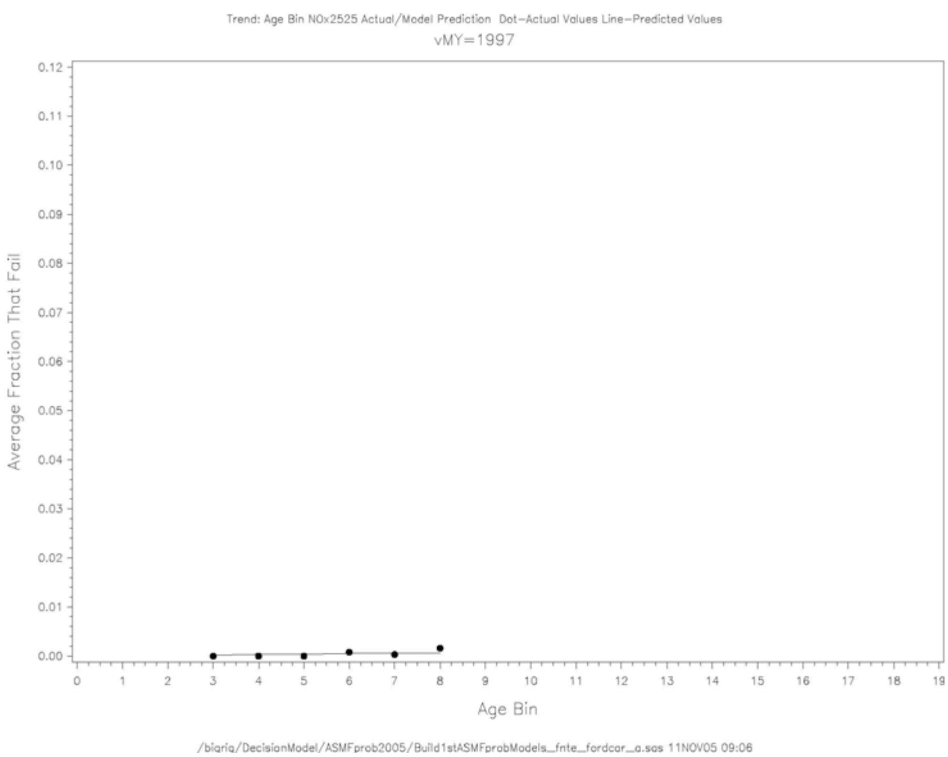


Figure M-13.

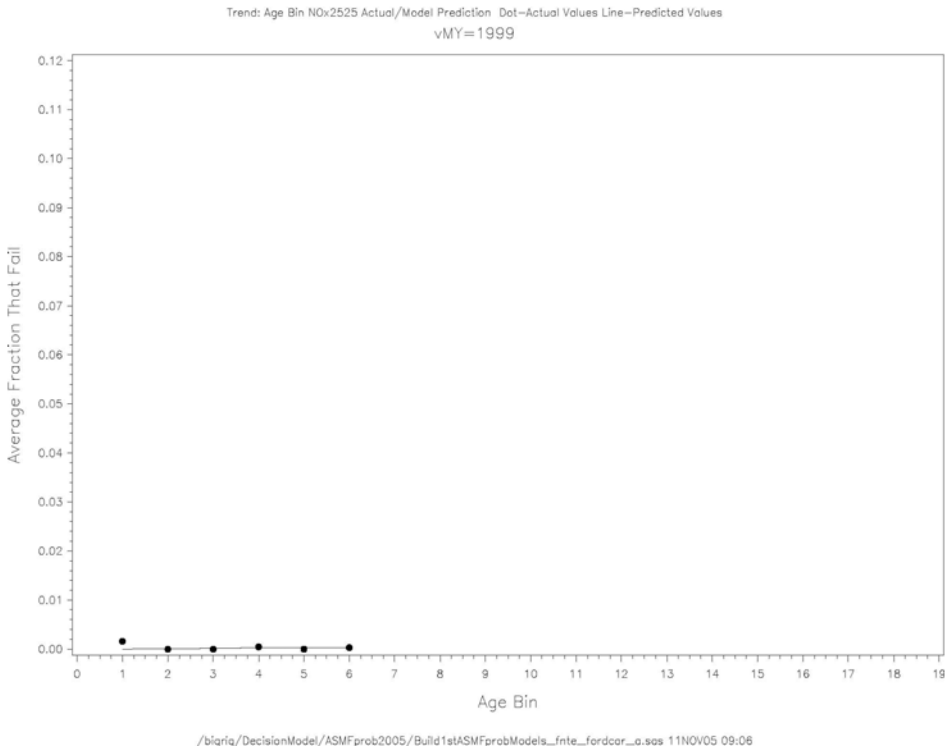


Figure M-14.

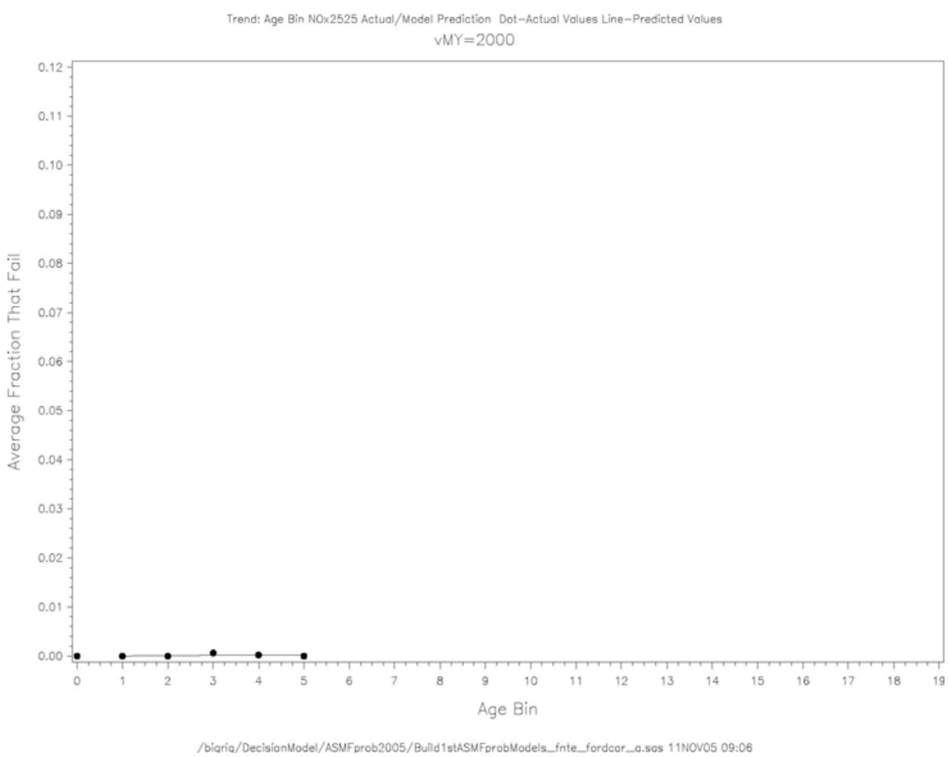


Figure M-15.

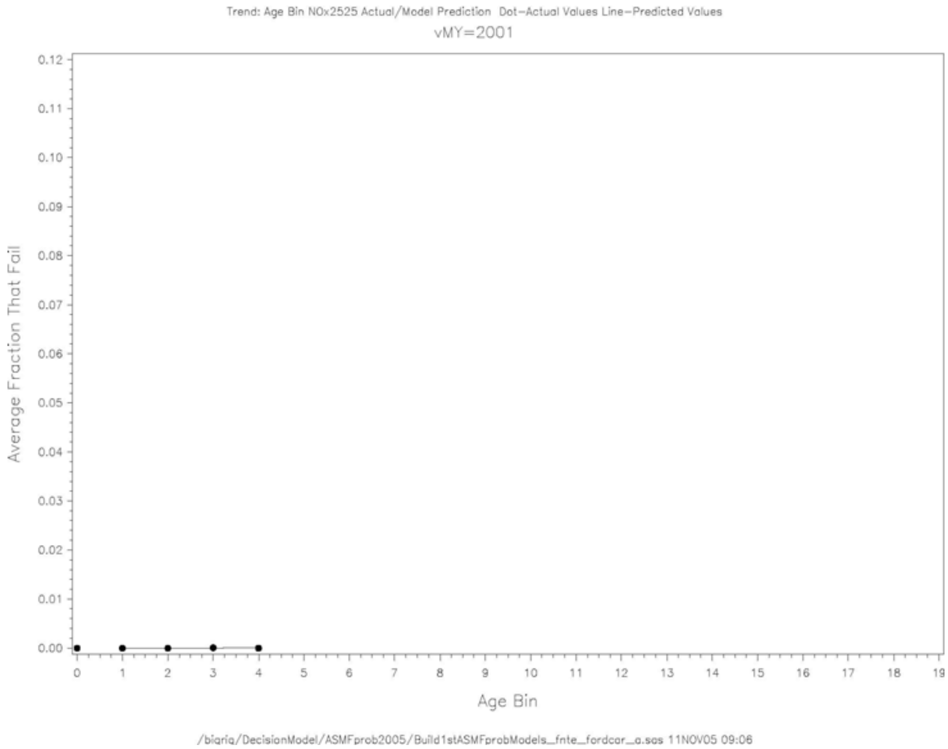


Figure M-16.

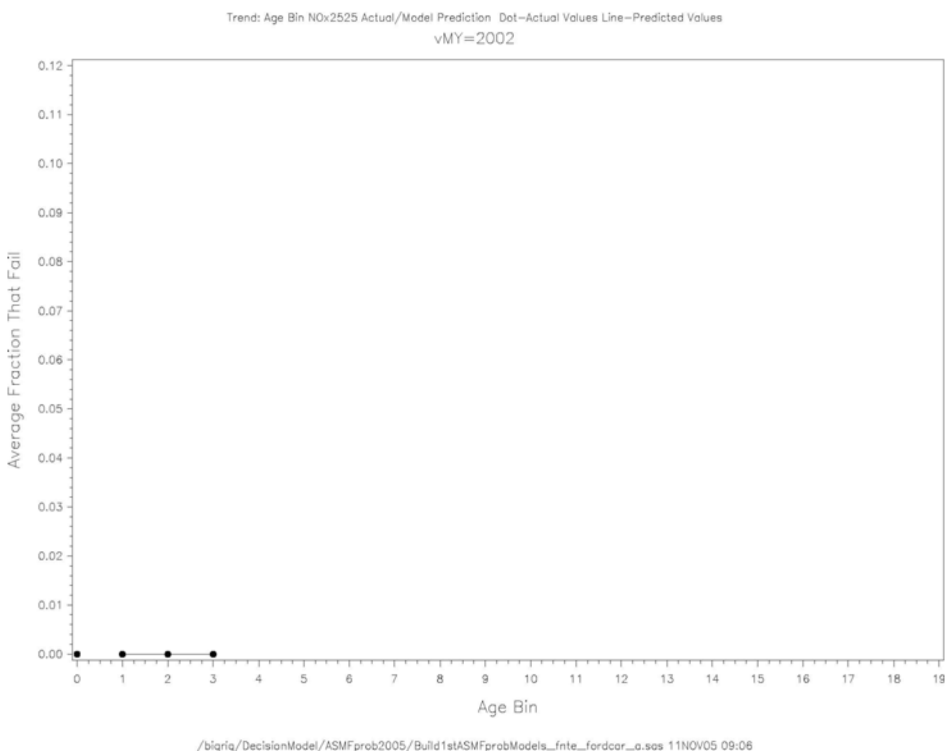
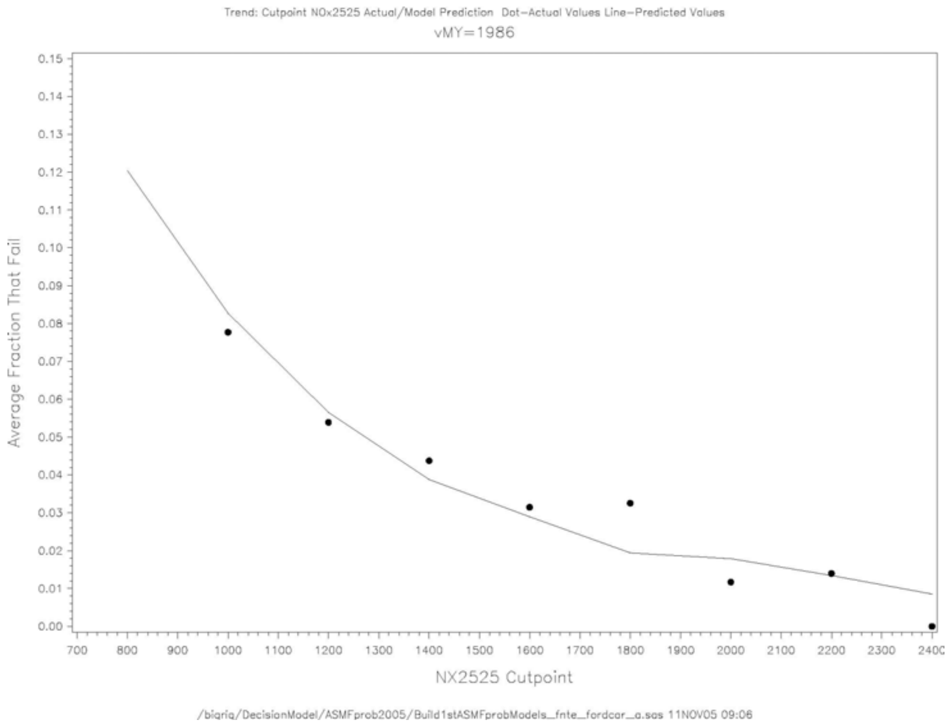


Figure M-17.



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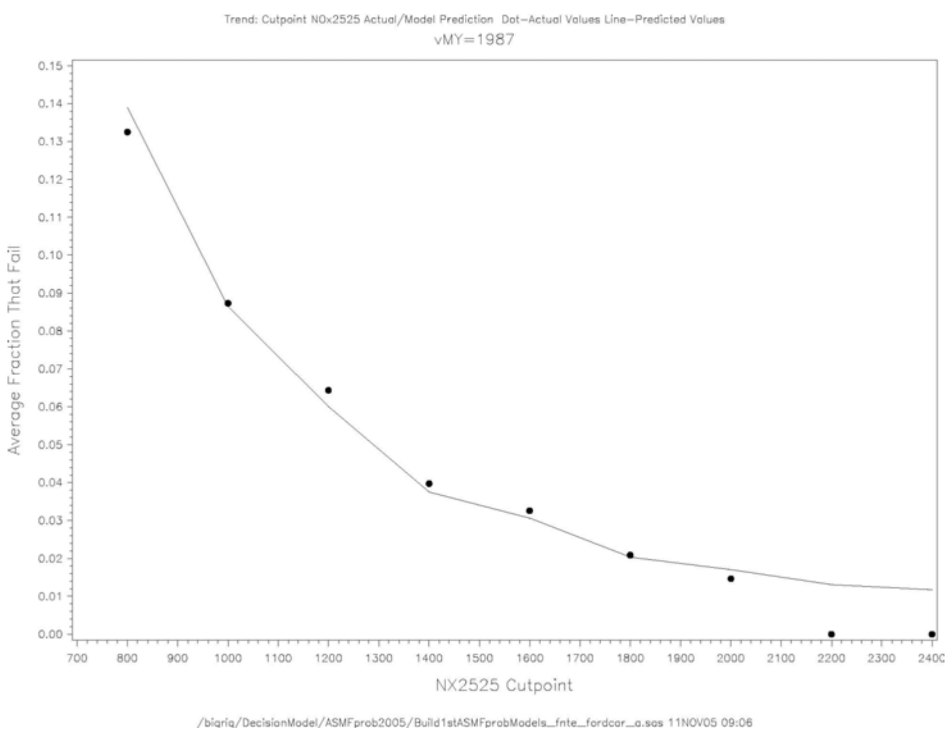

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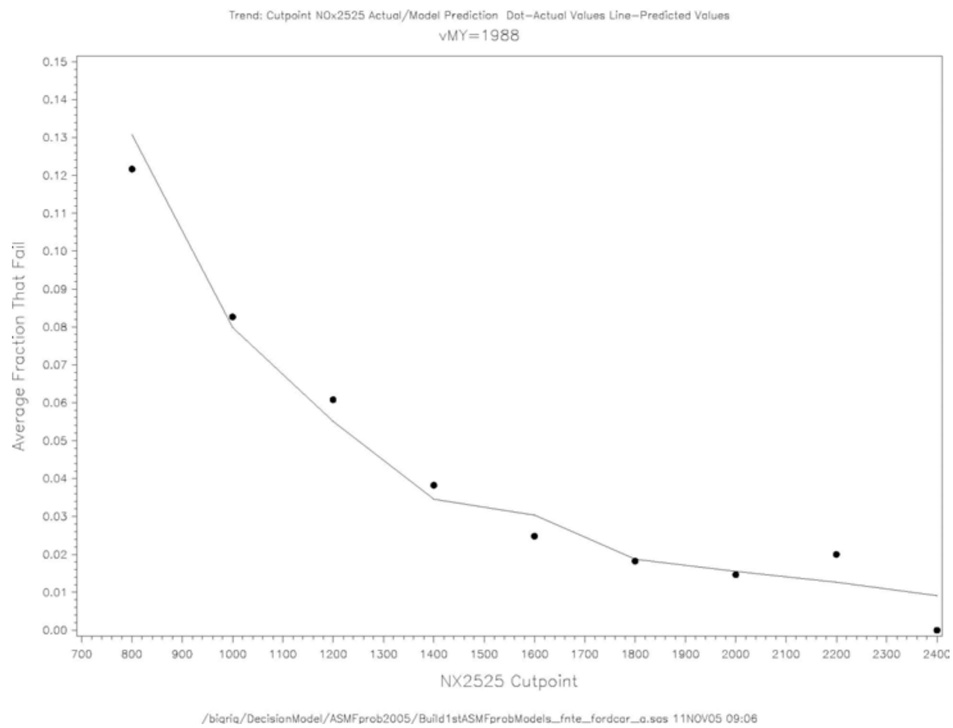

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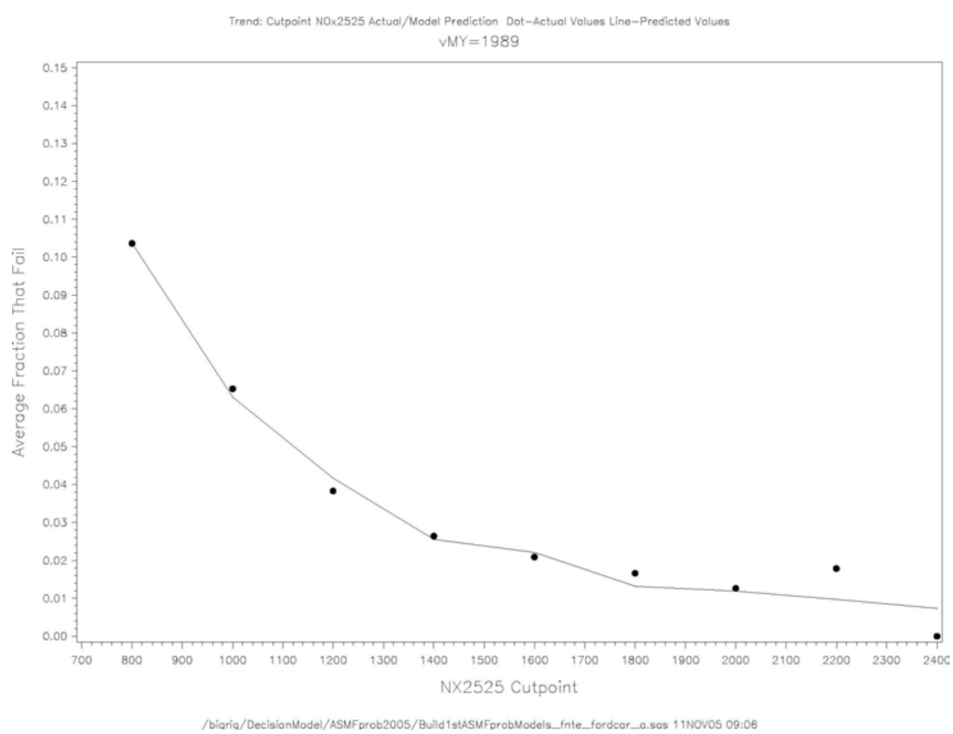

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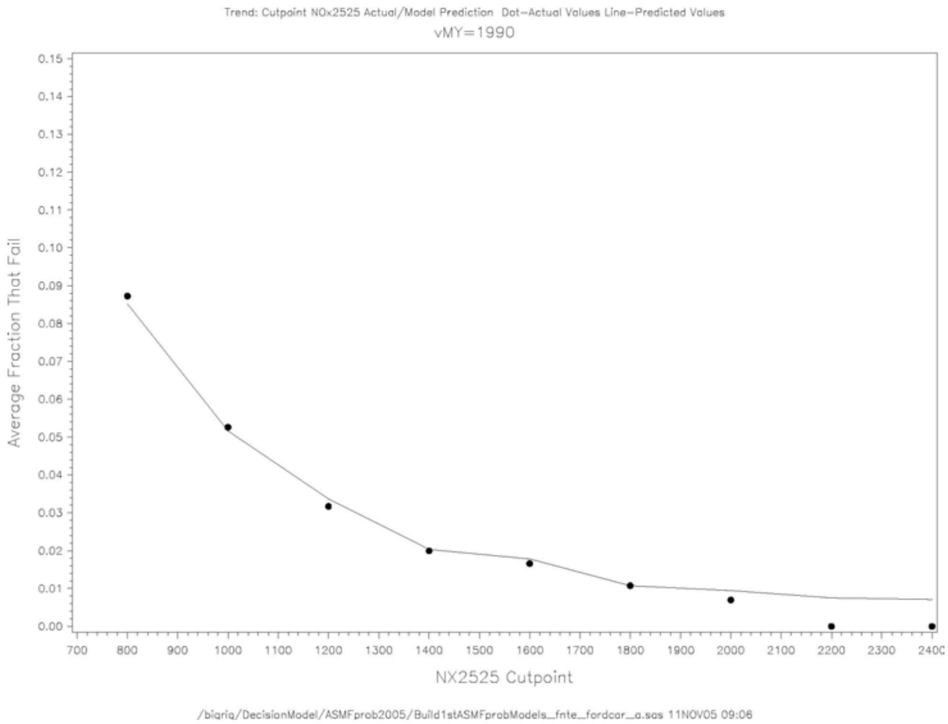

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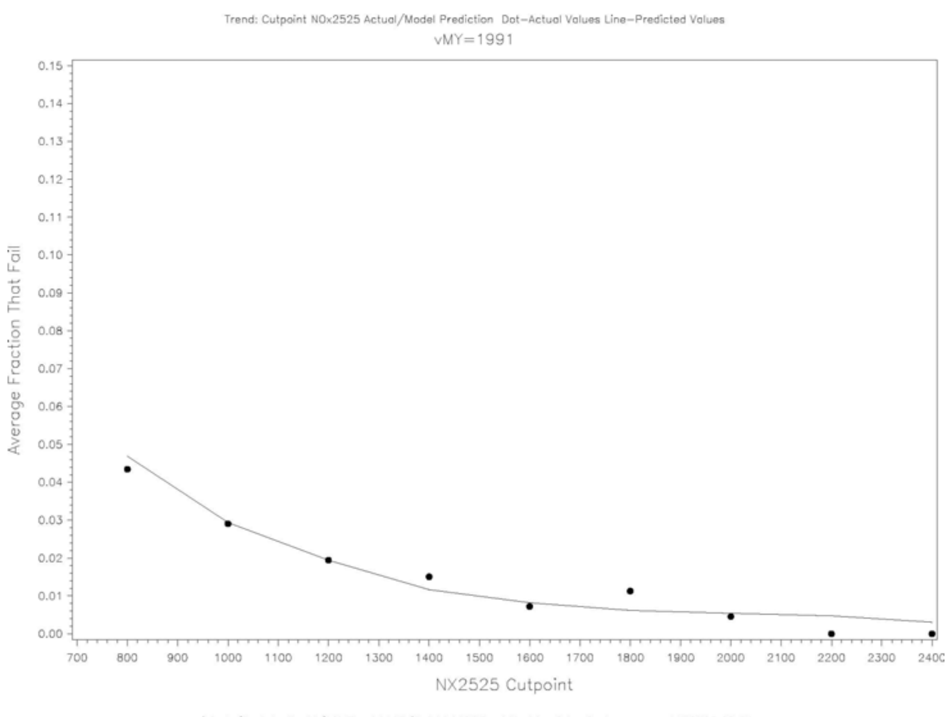

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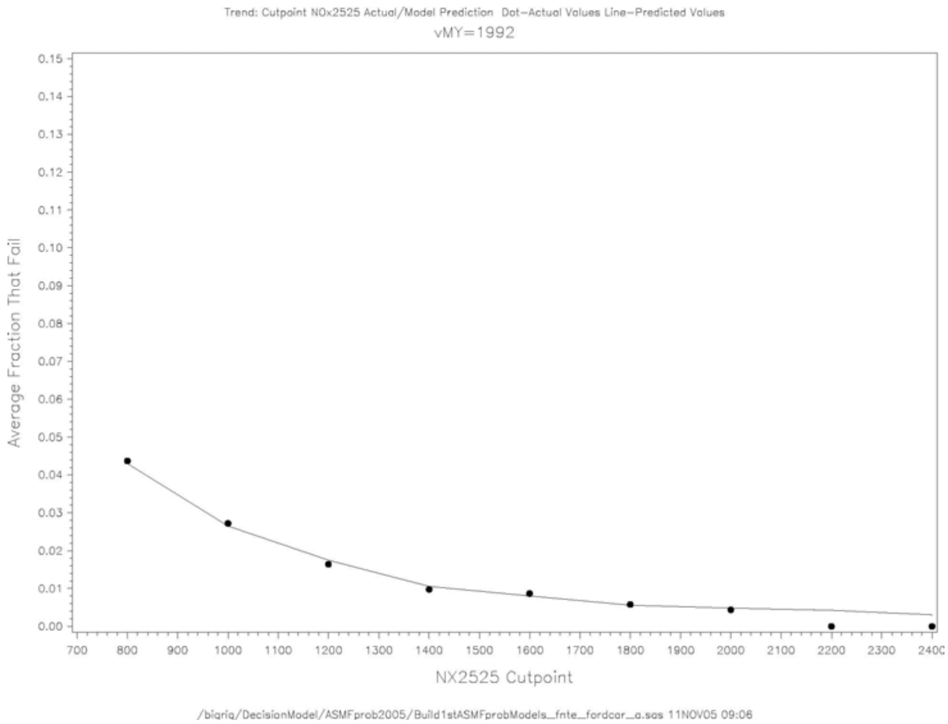

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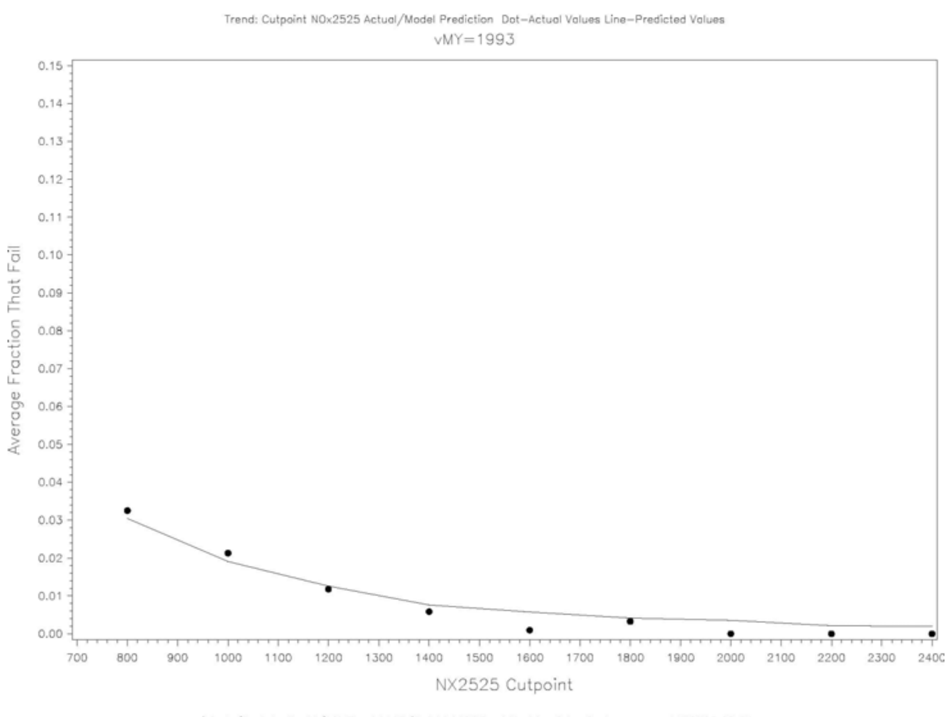

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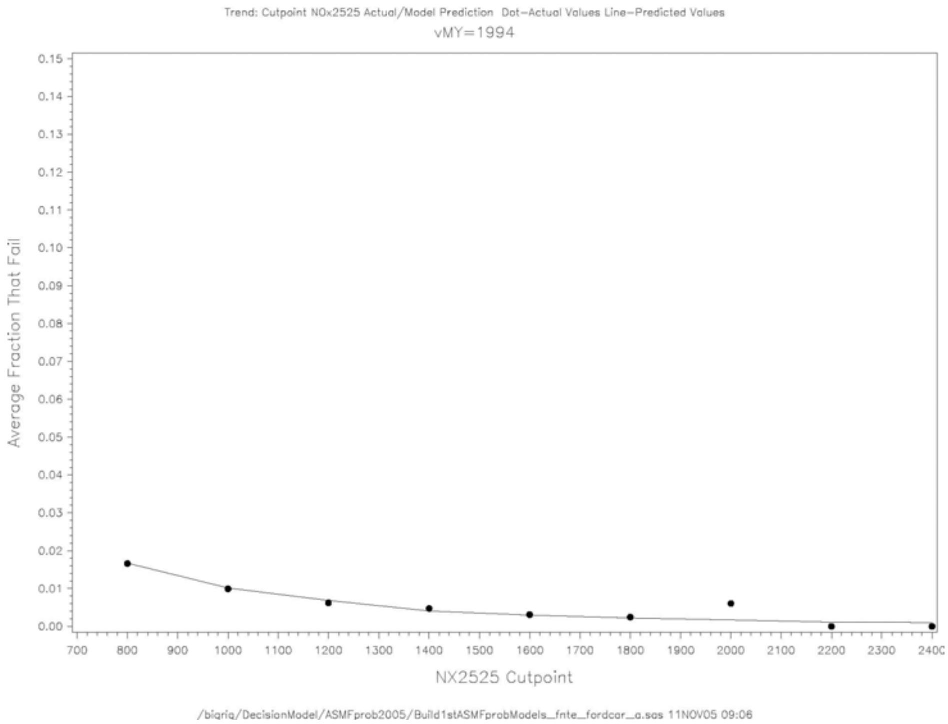

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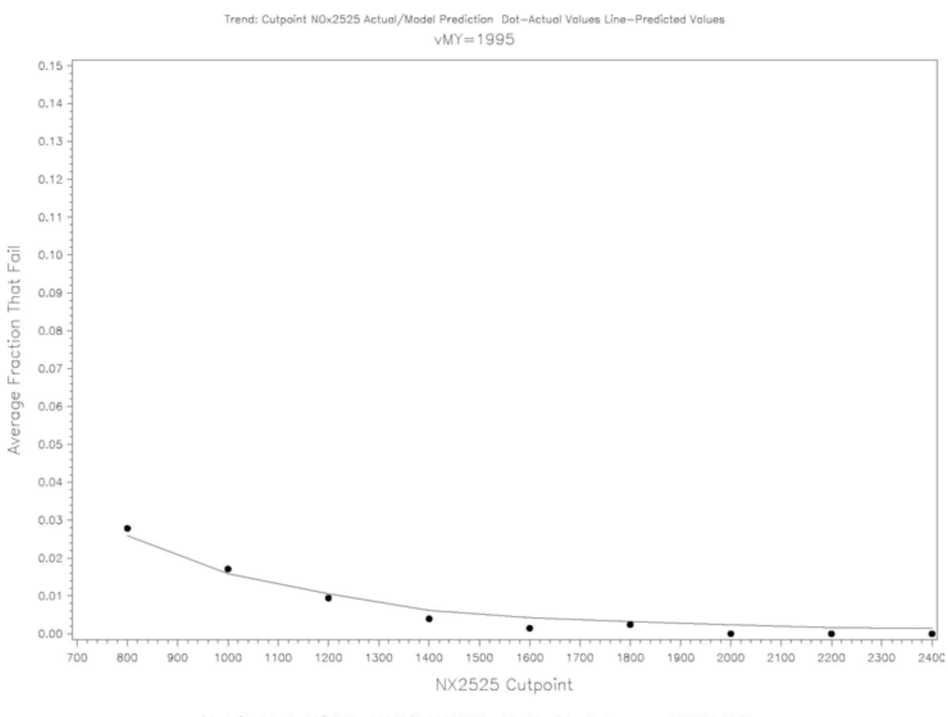

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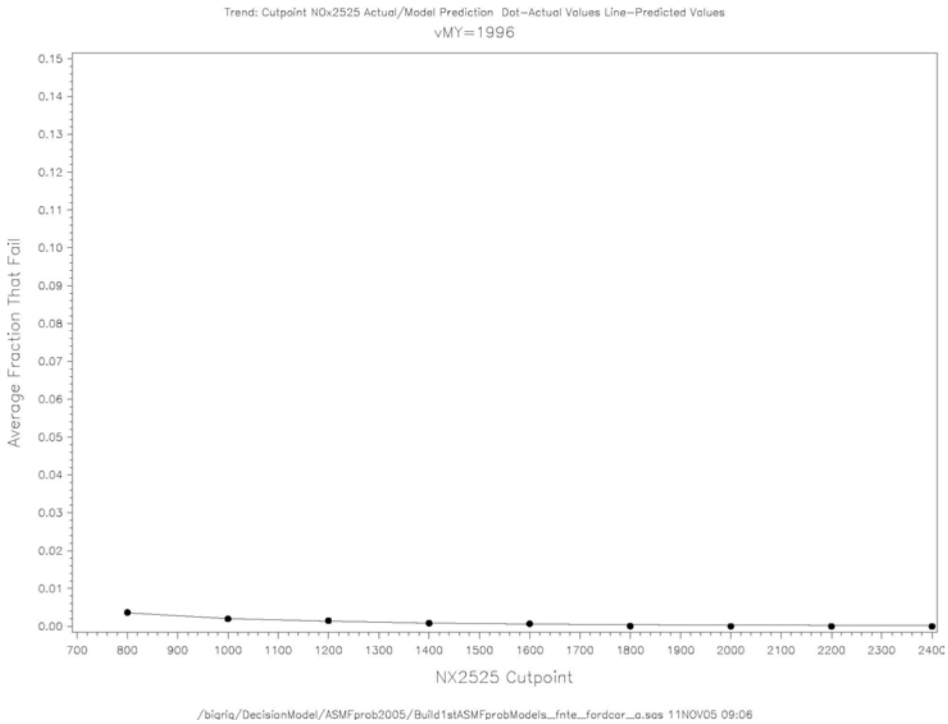

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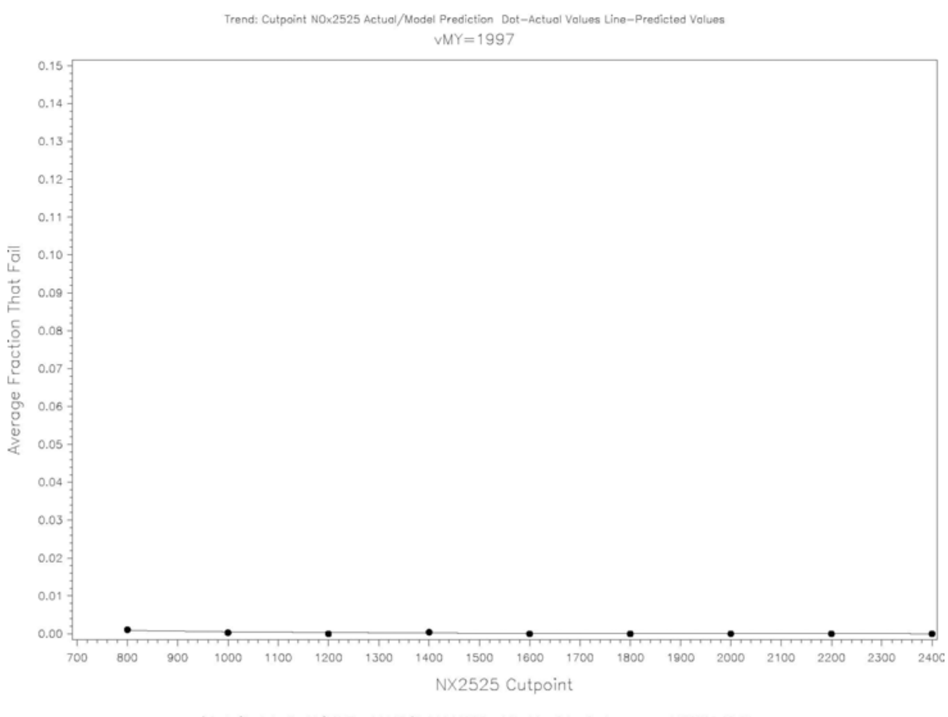

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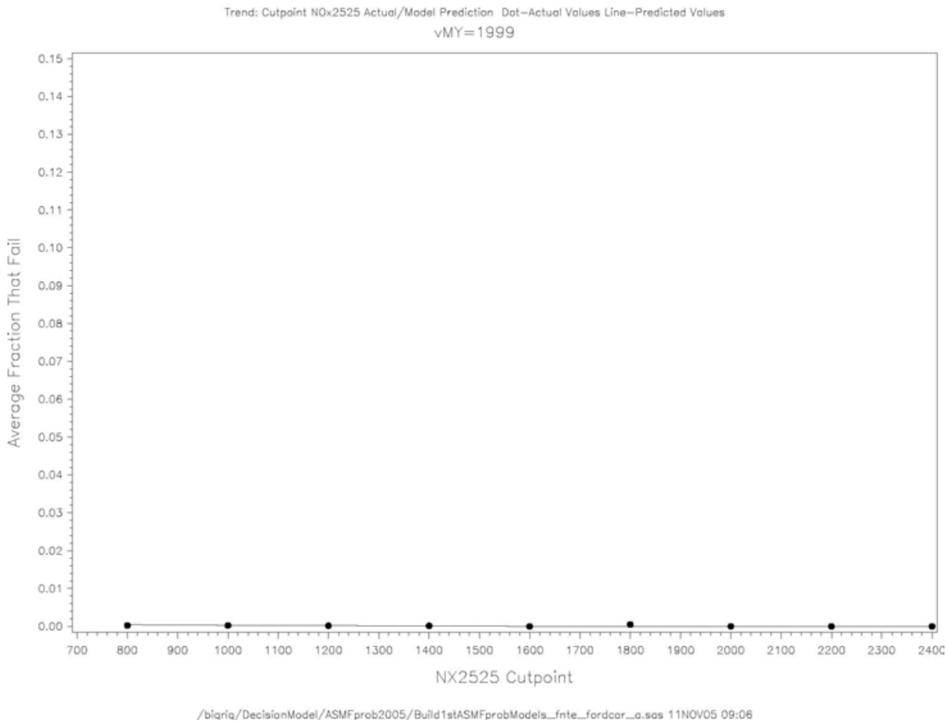

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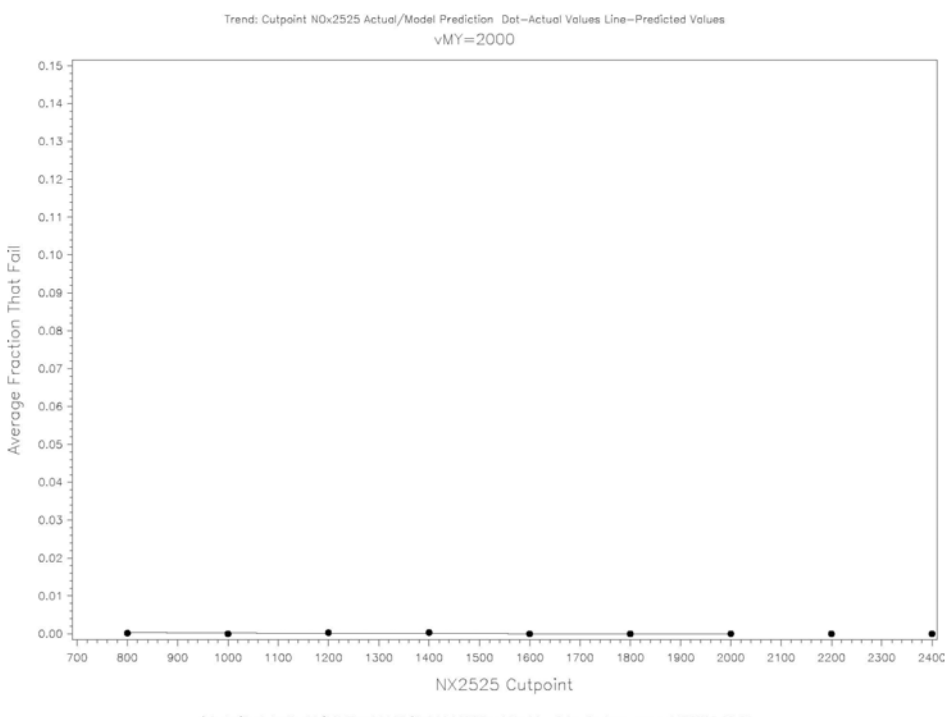

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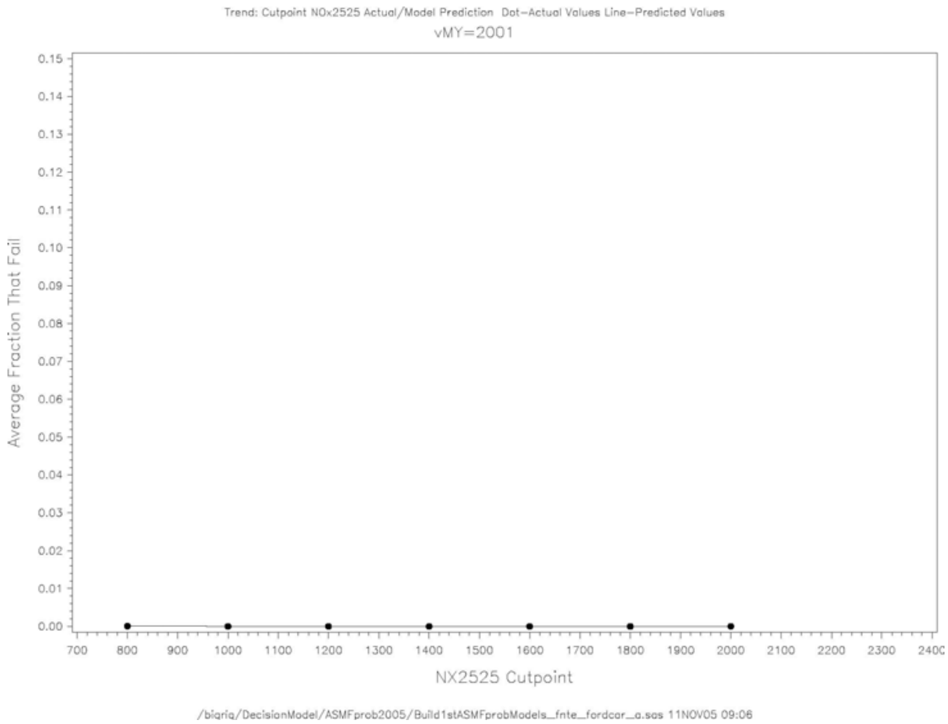

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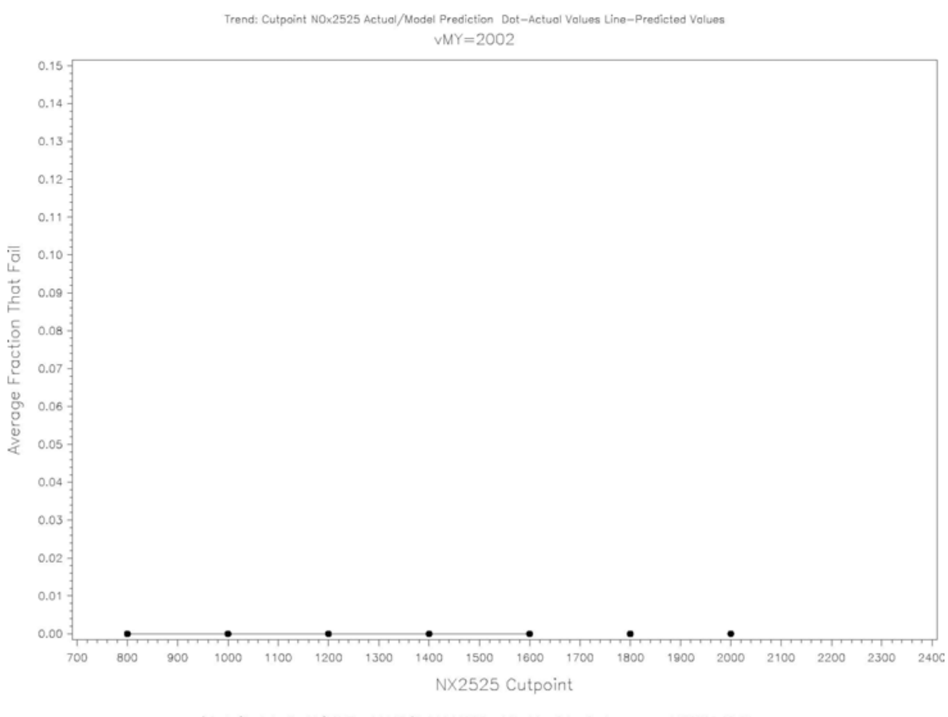

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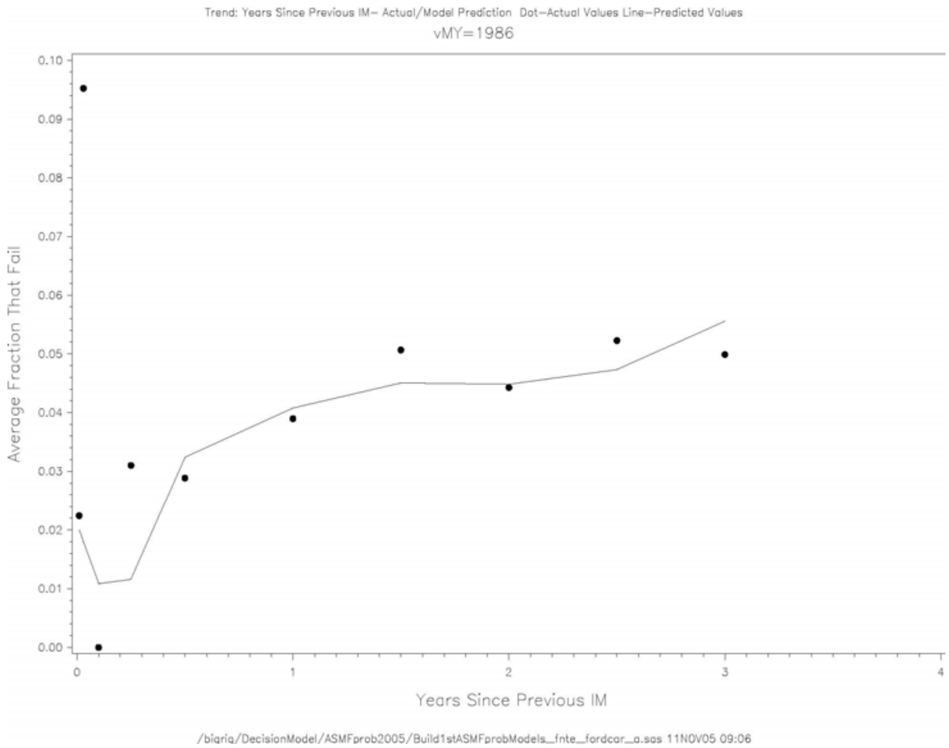

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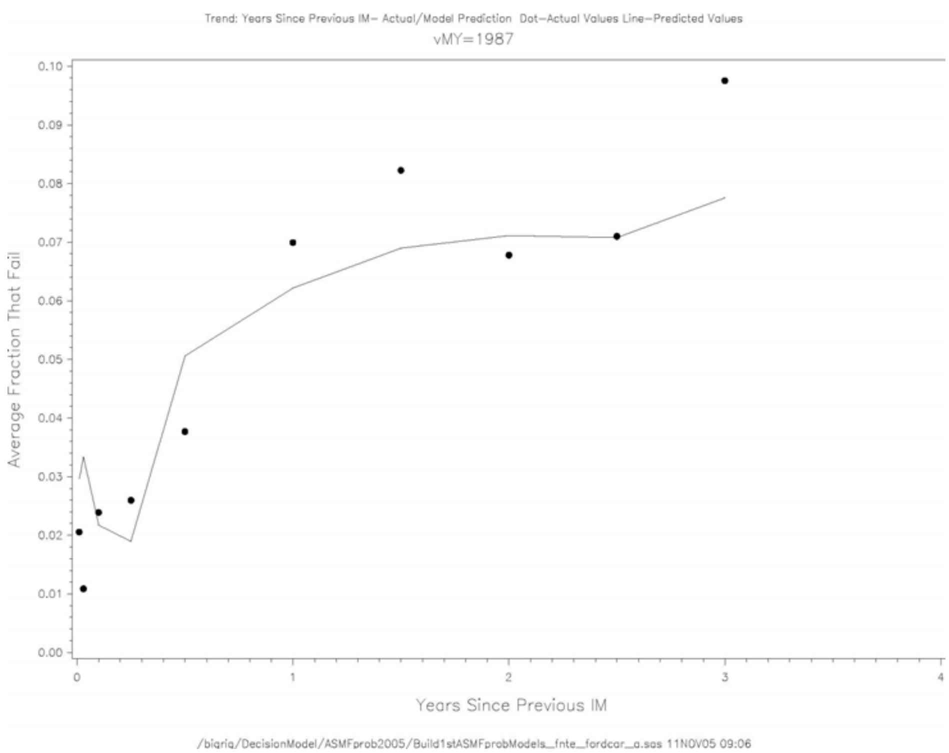

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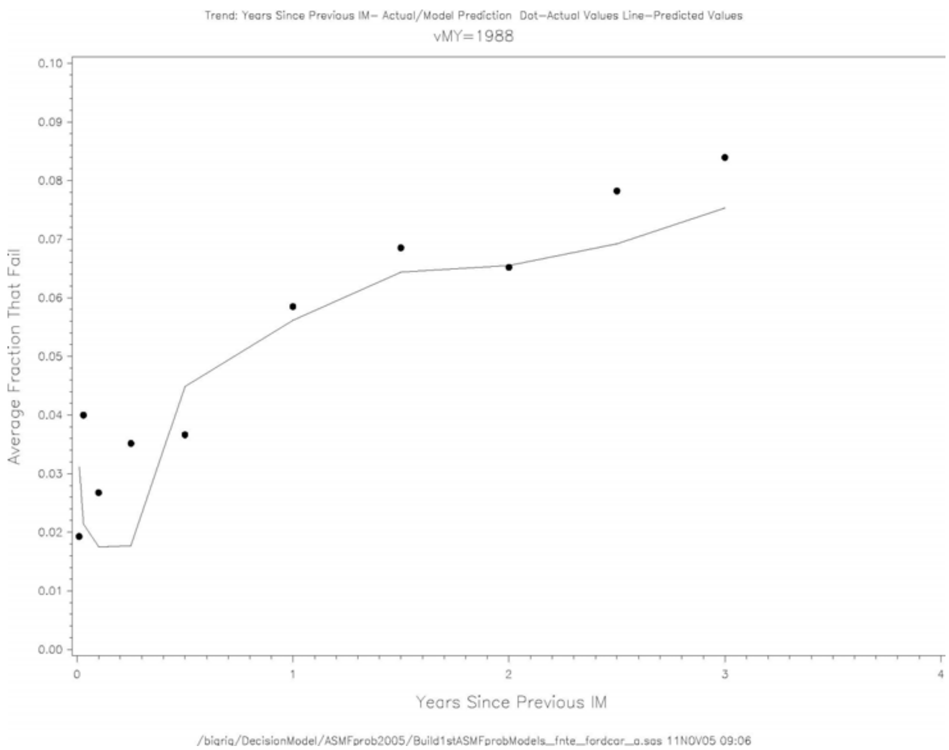

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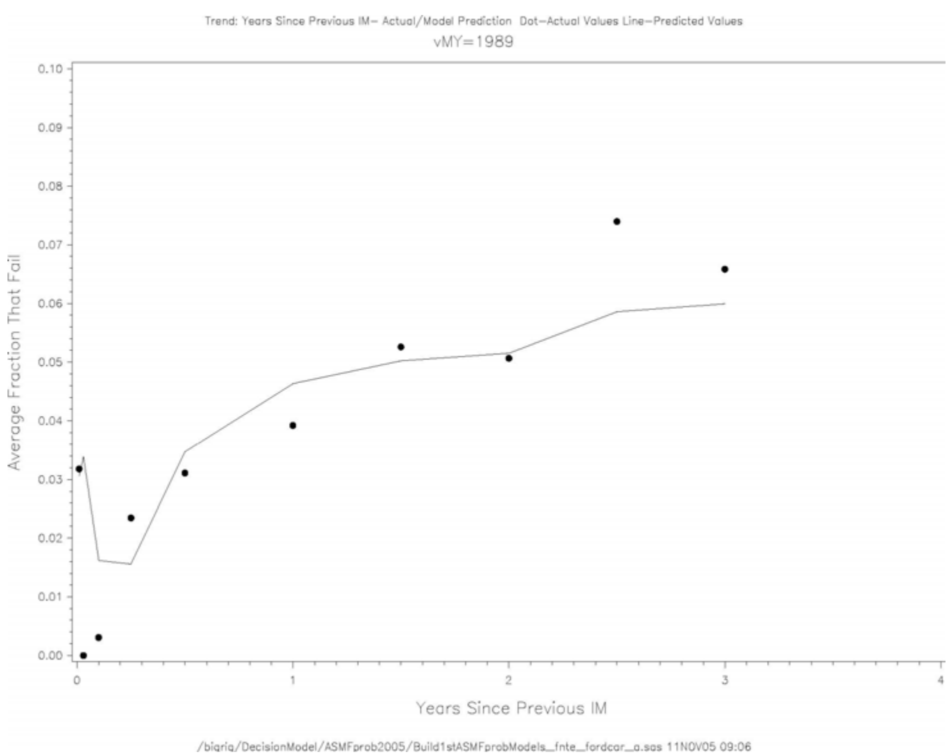

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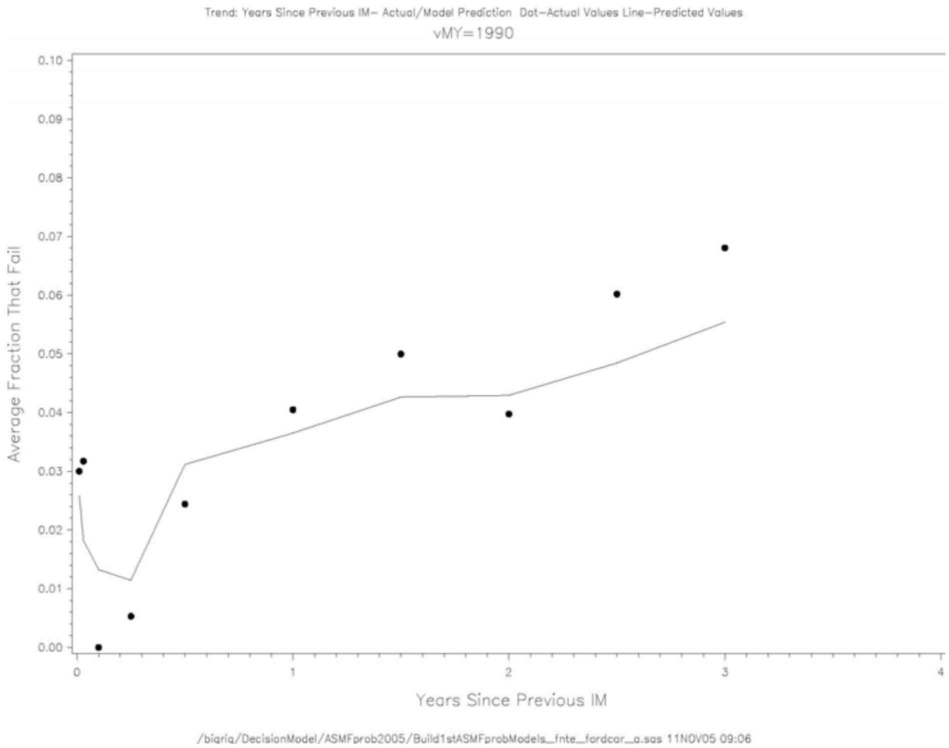

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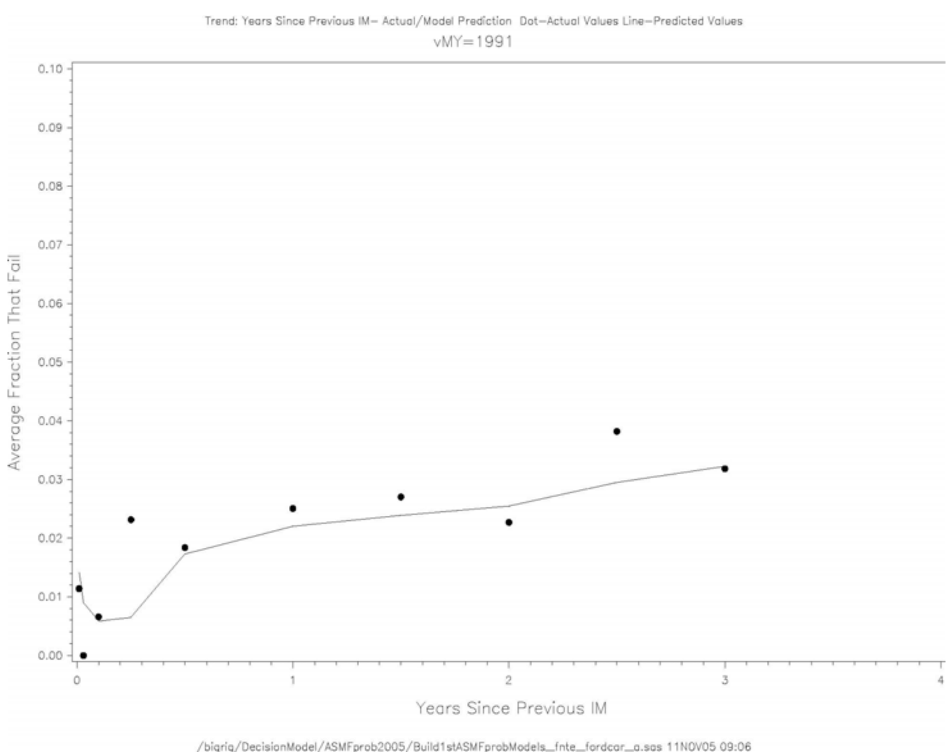

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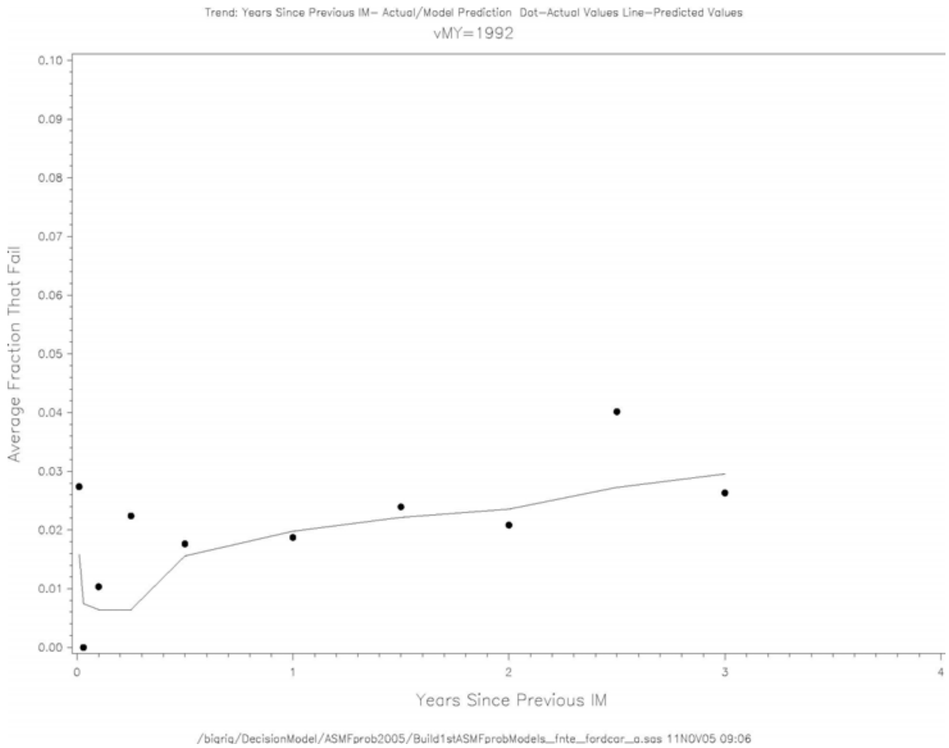

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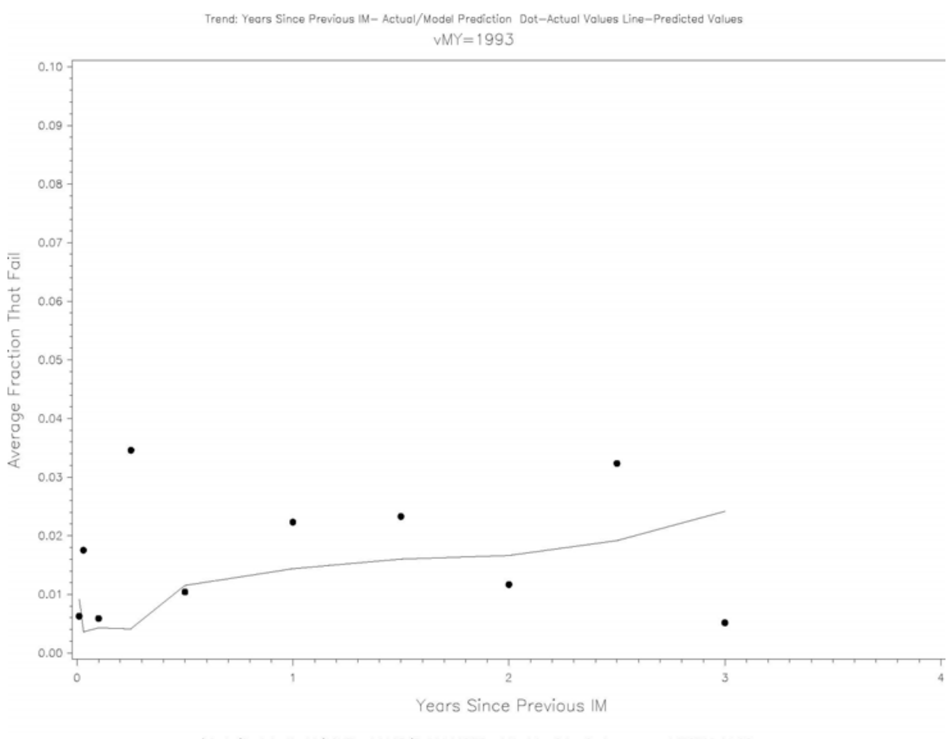

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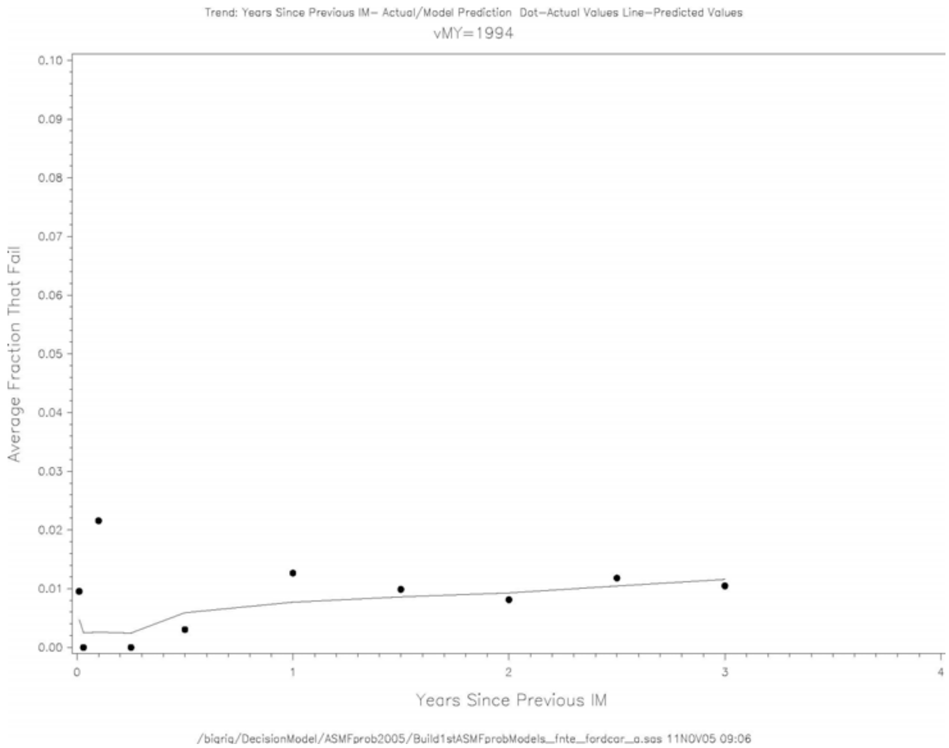

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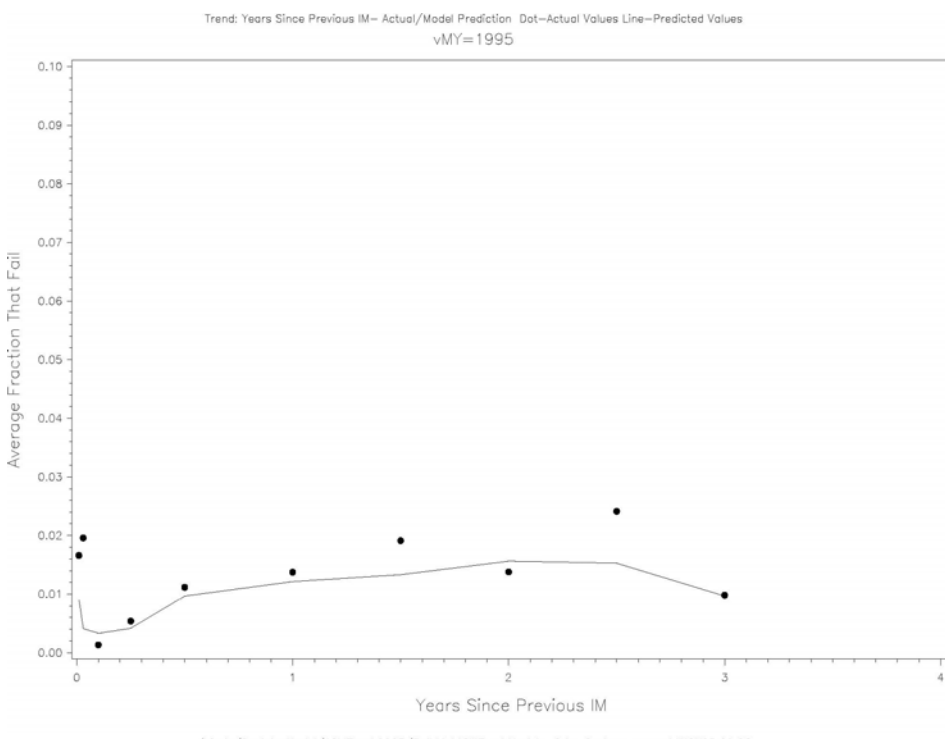

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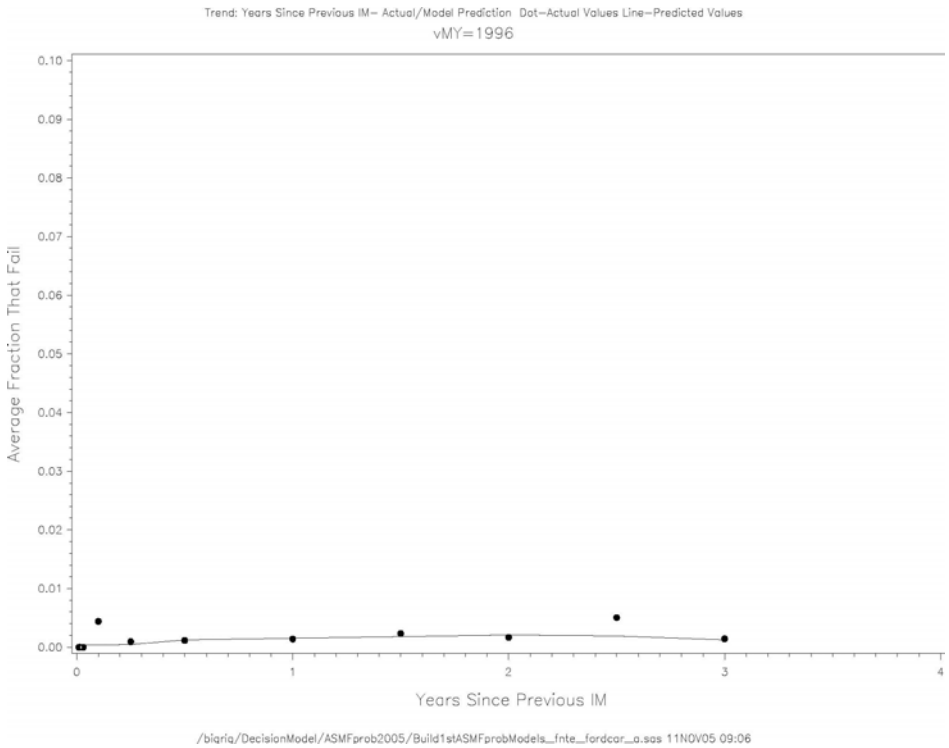

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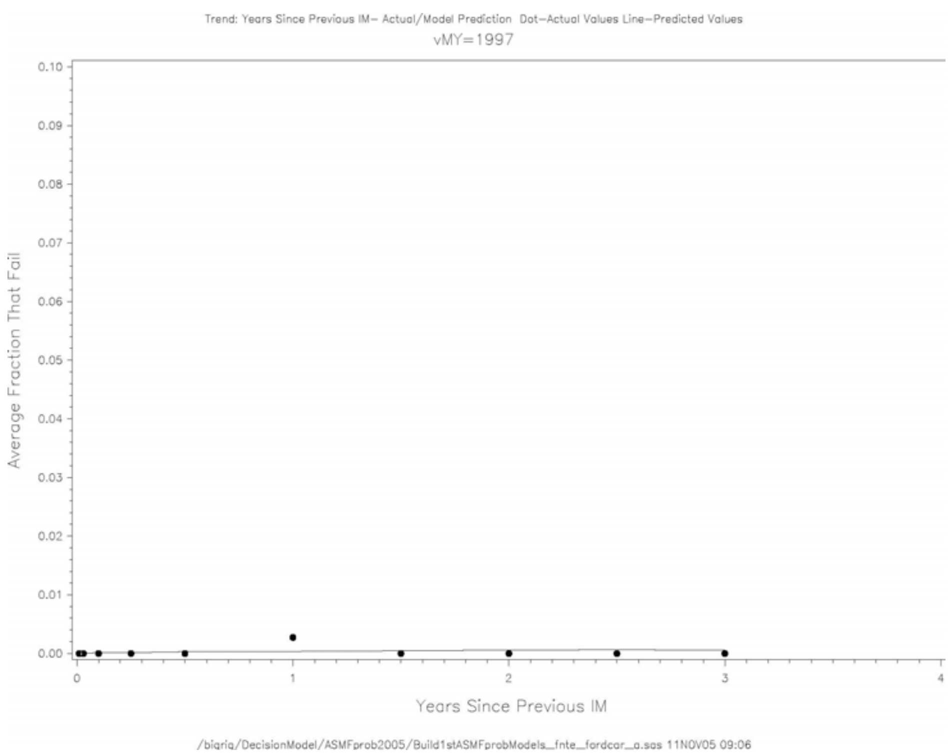

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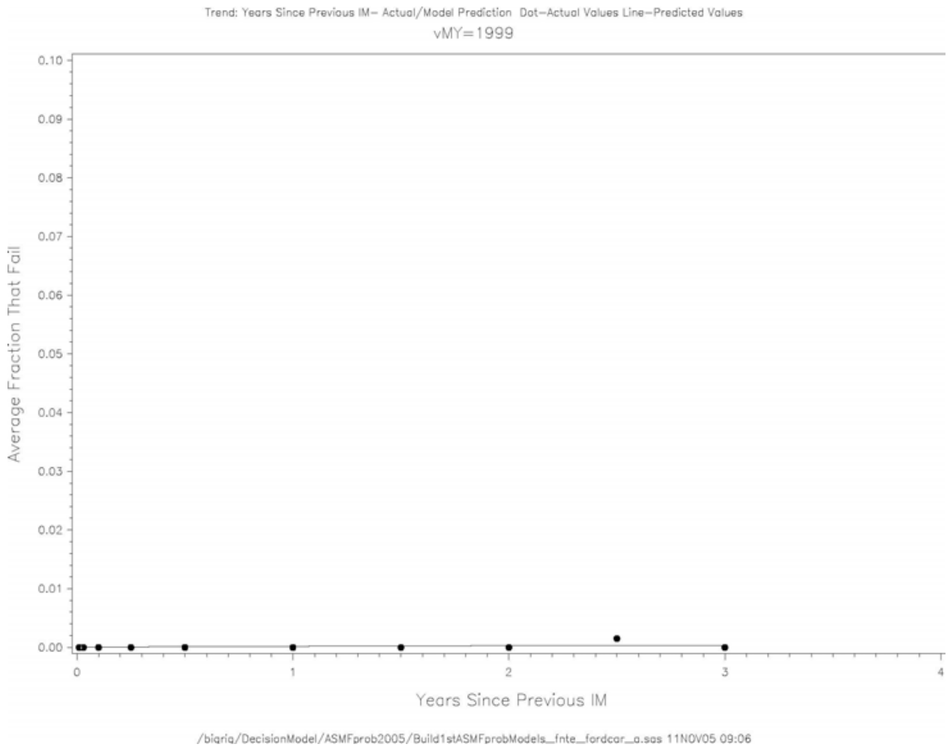

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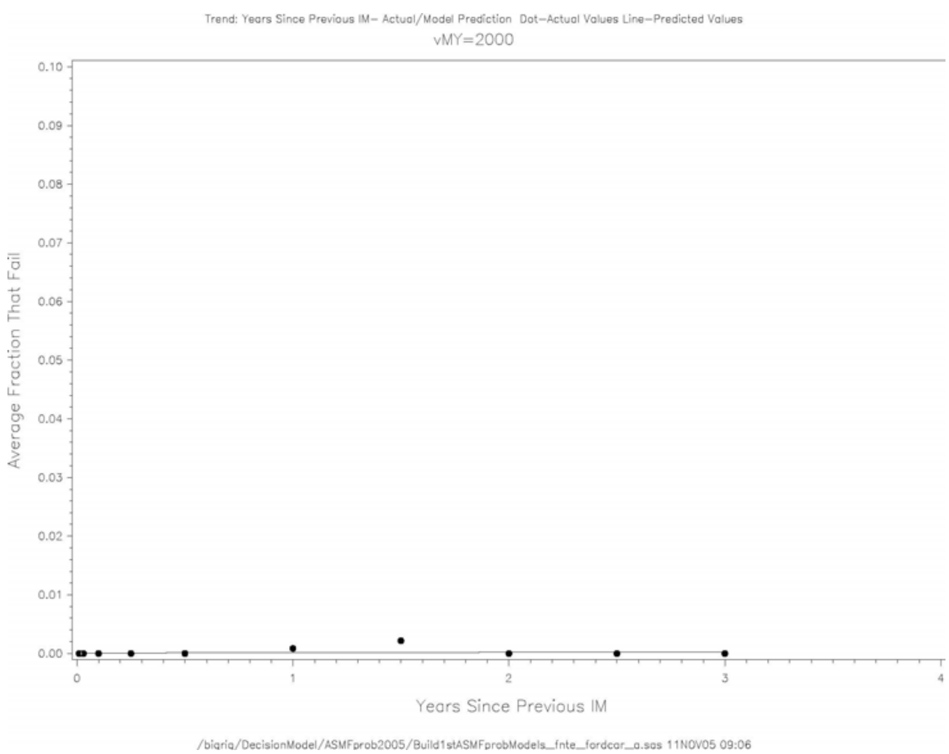

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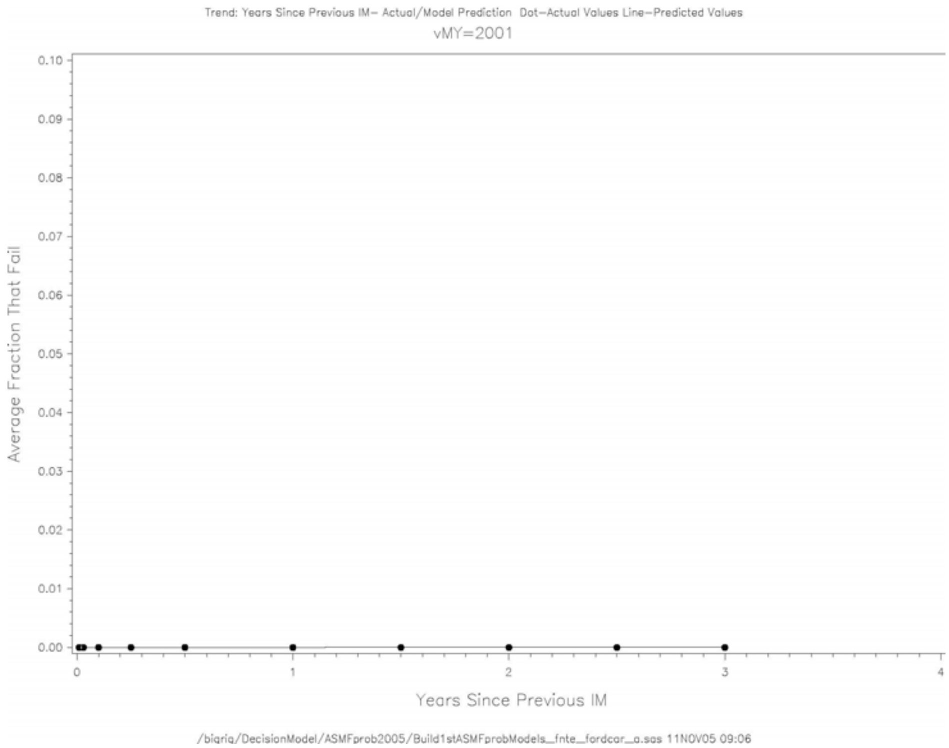

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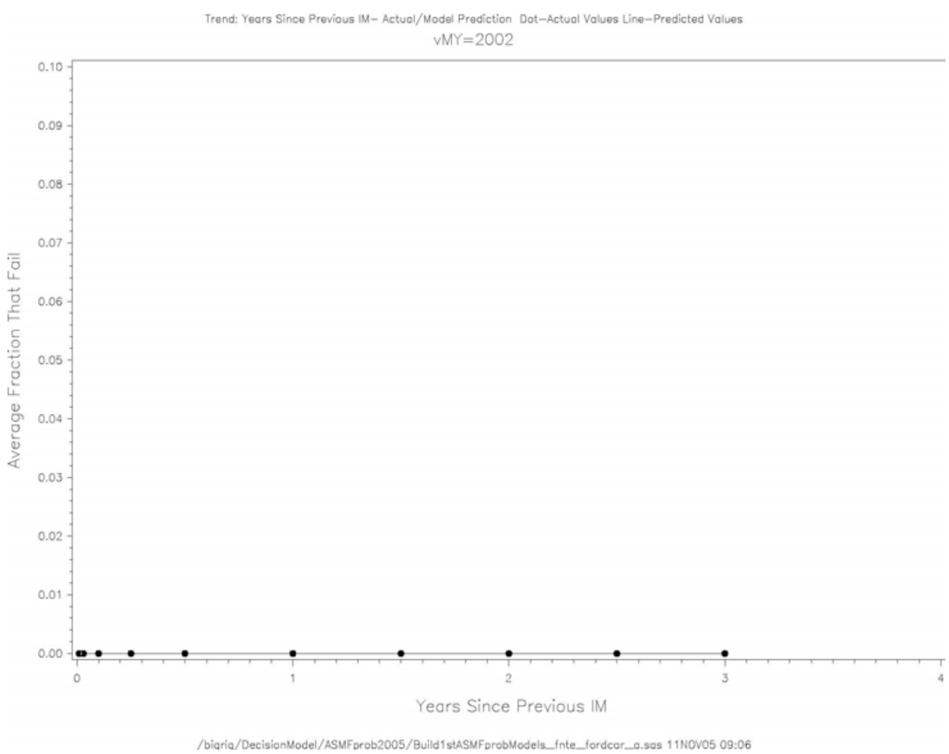

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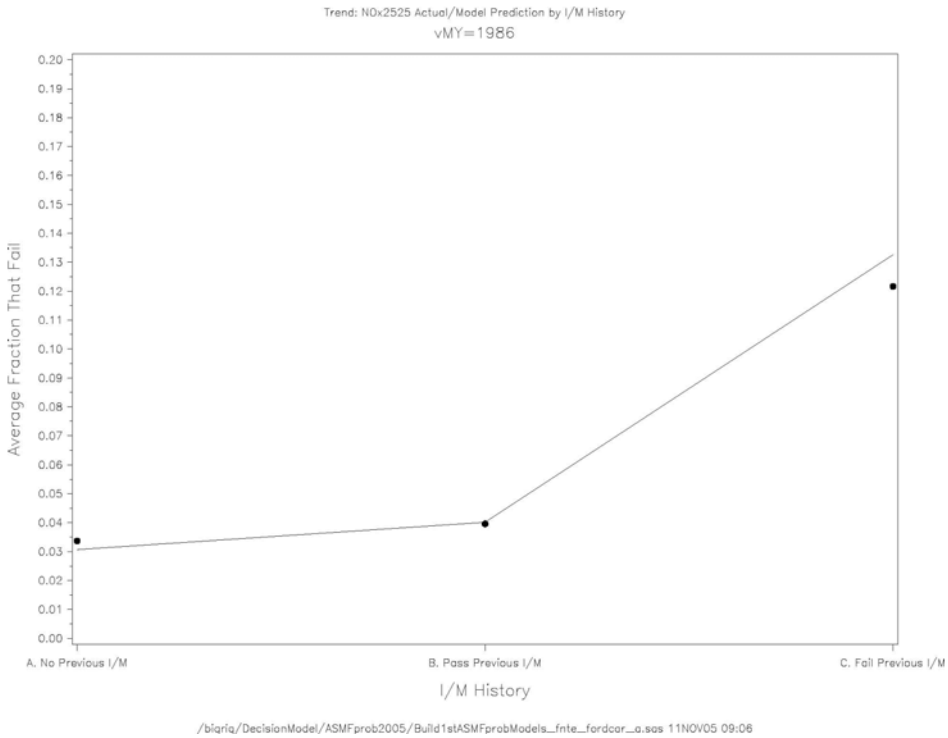

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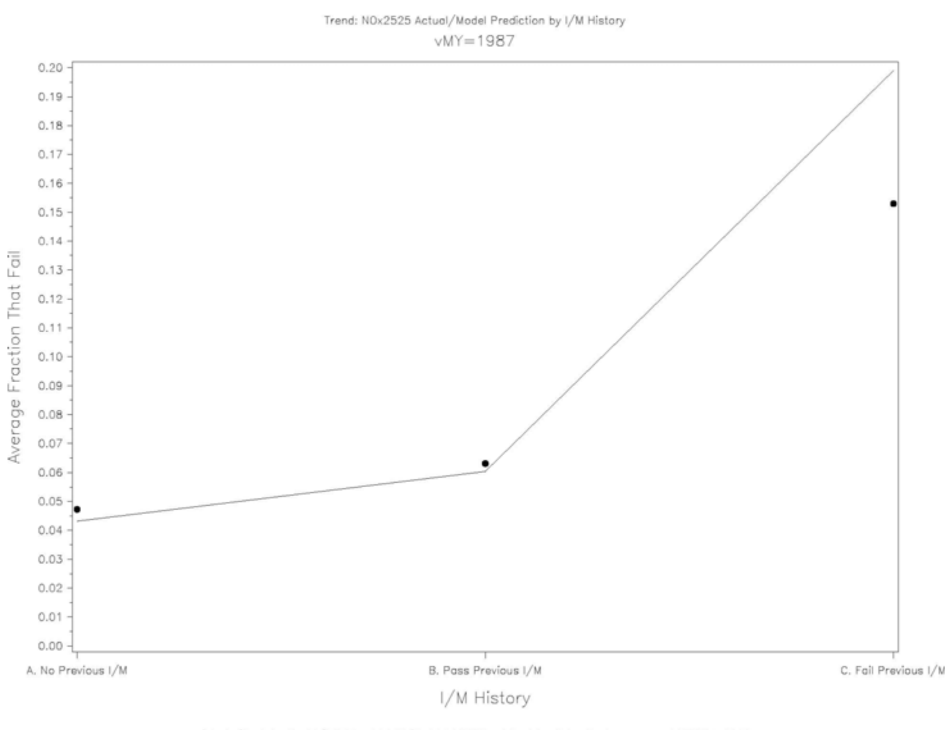

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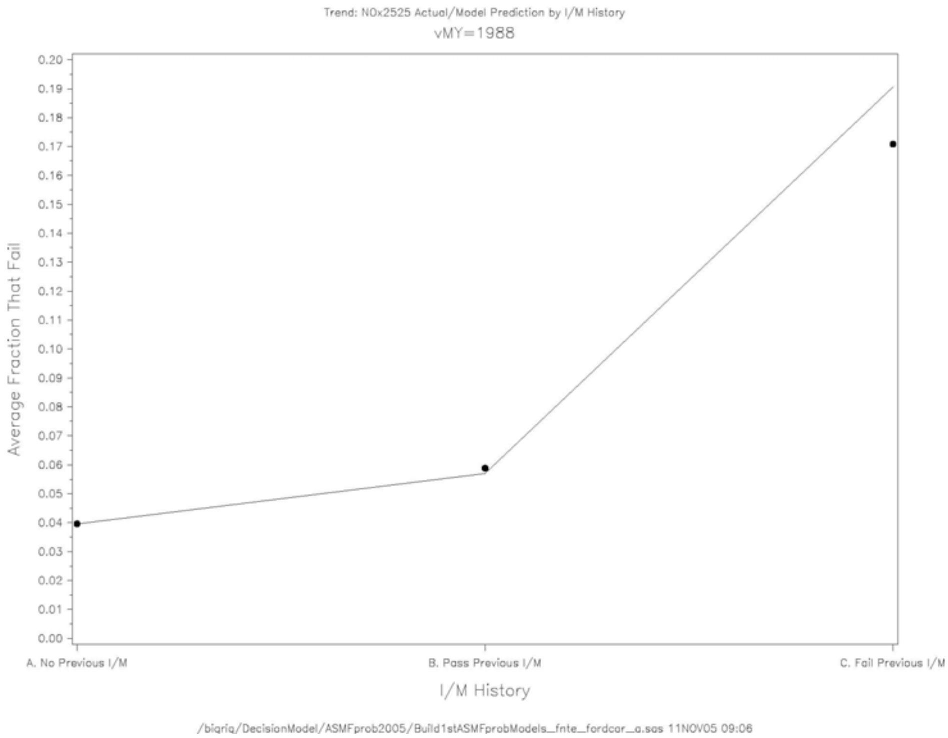

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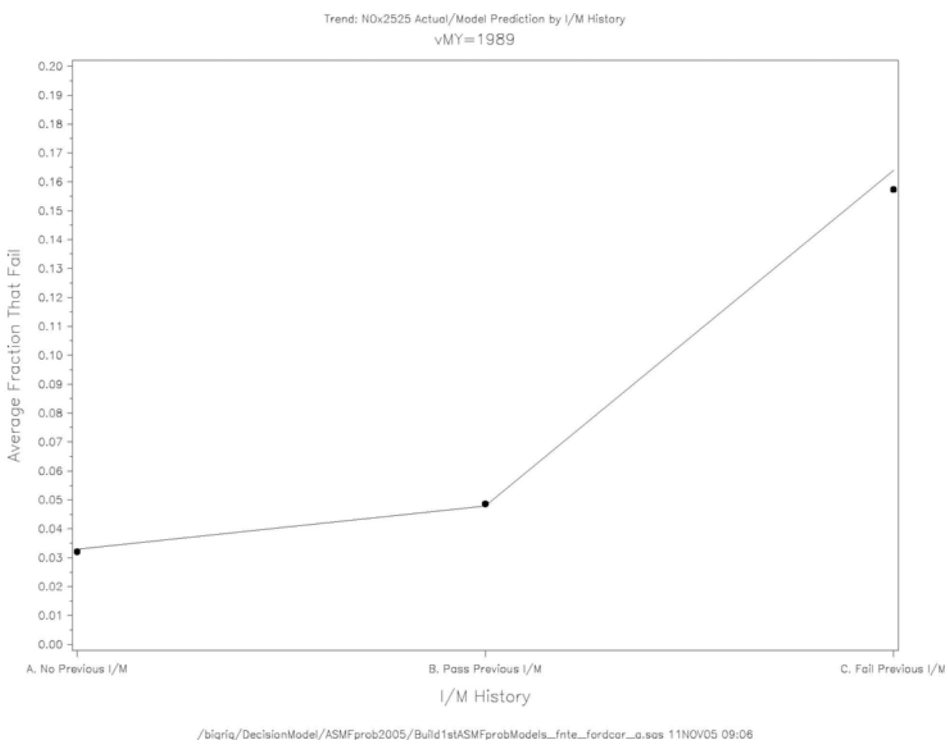

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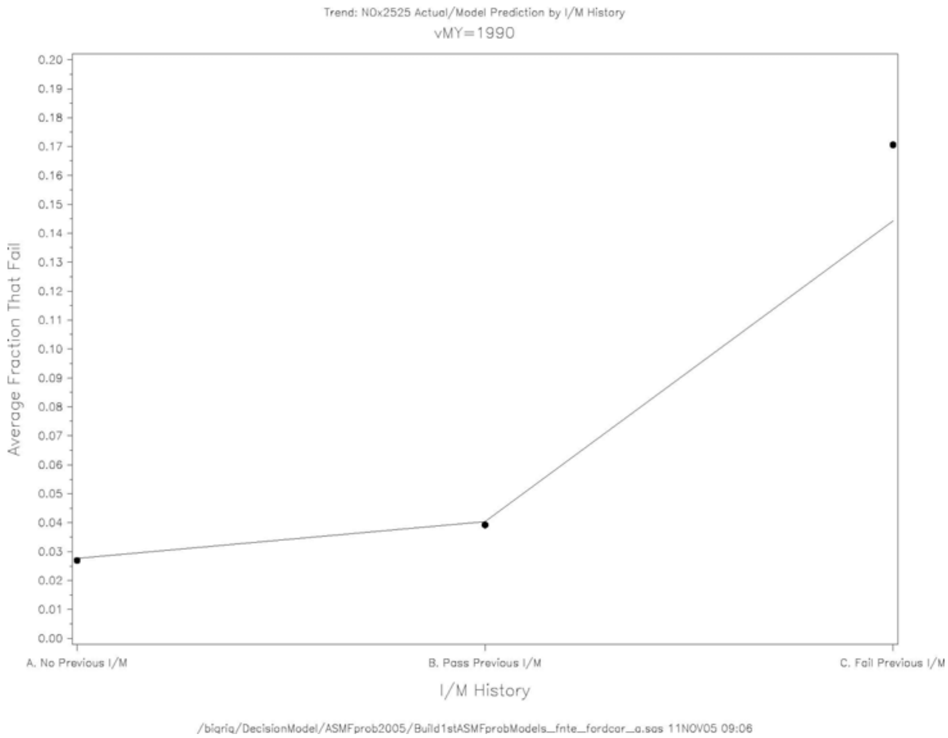

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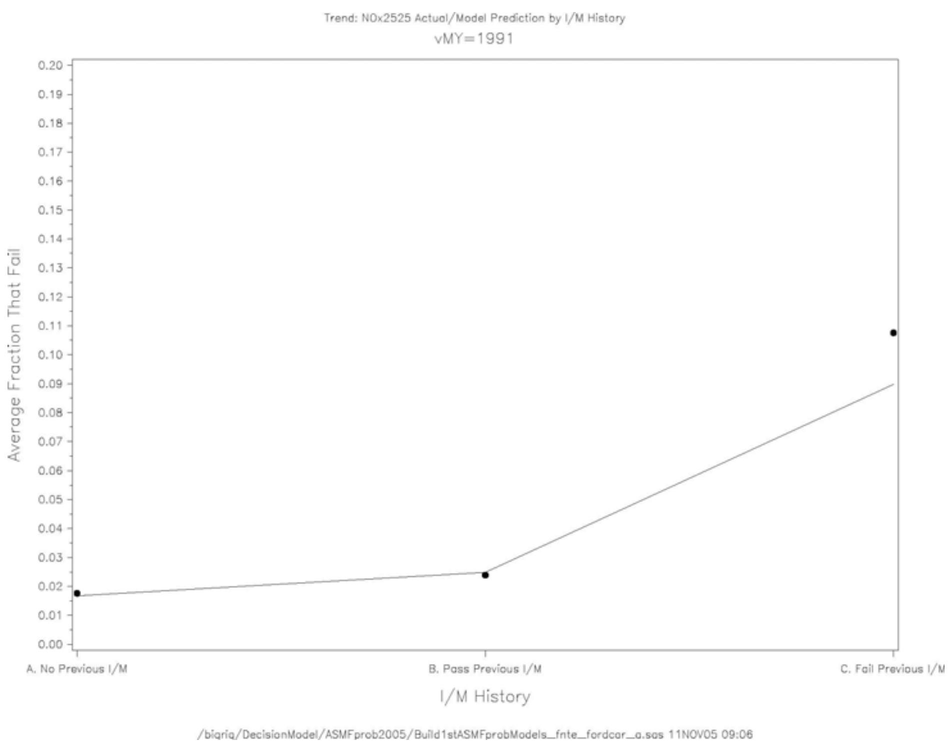

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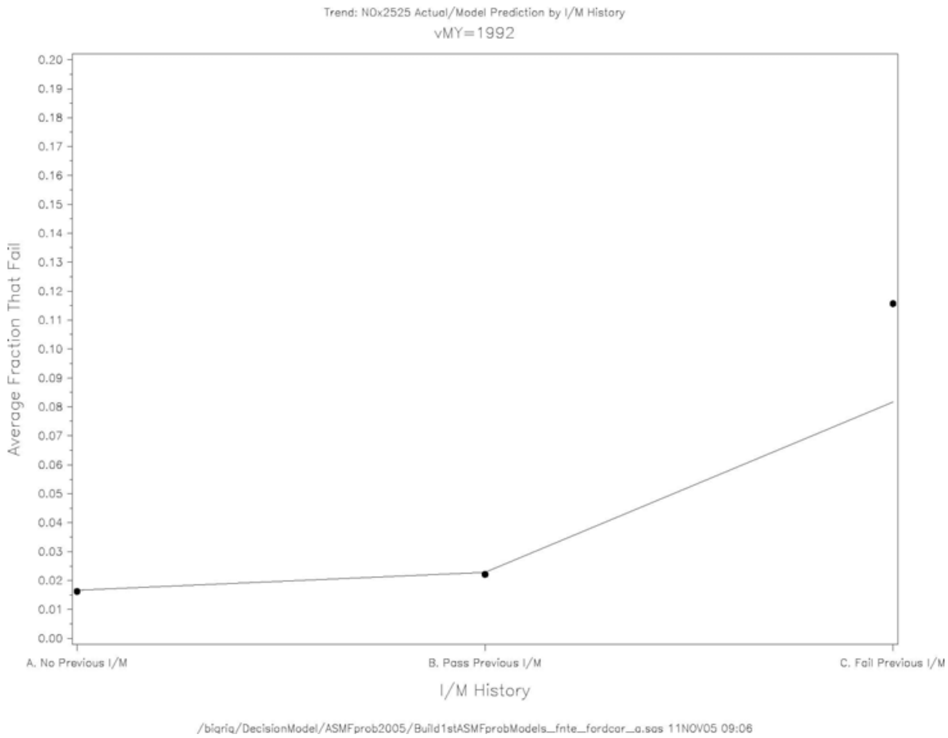

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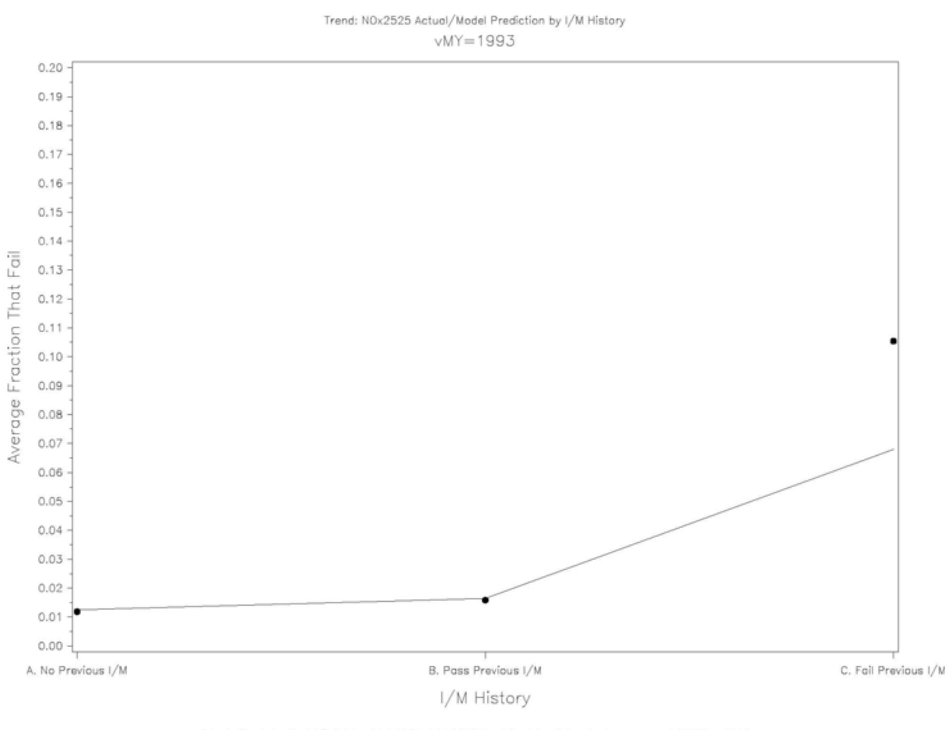

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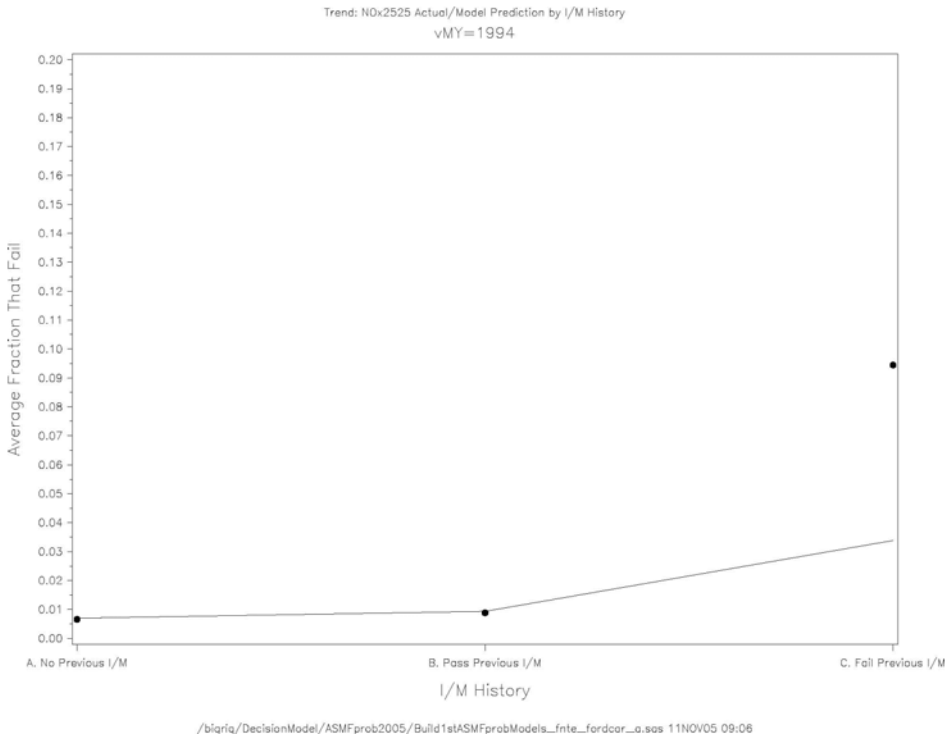

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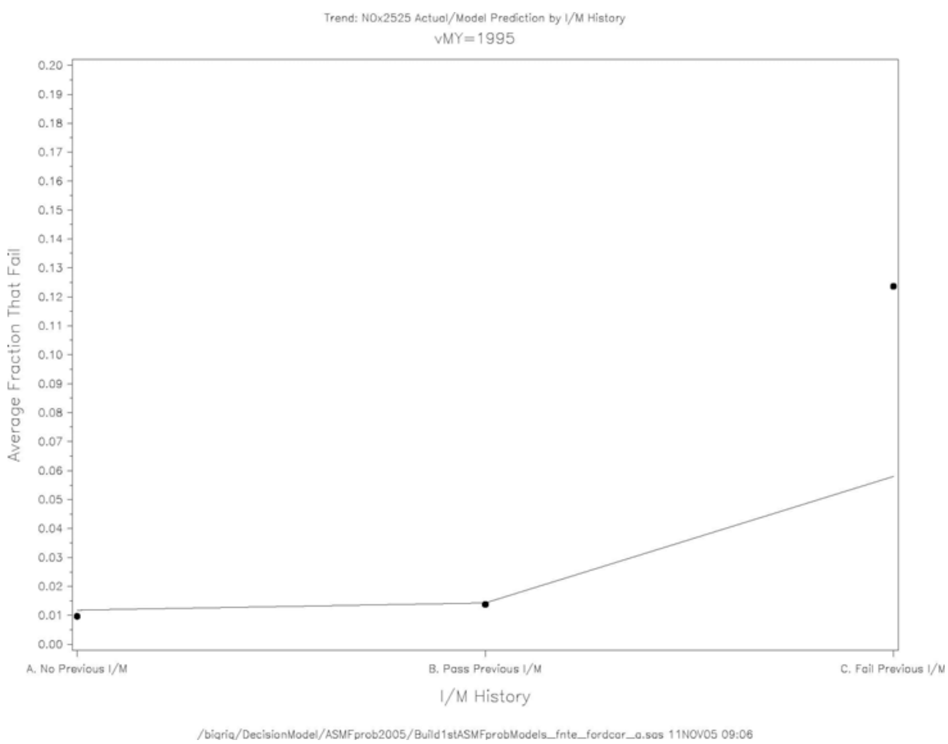

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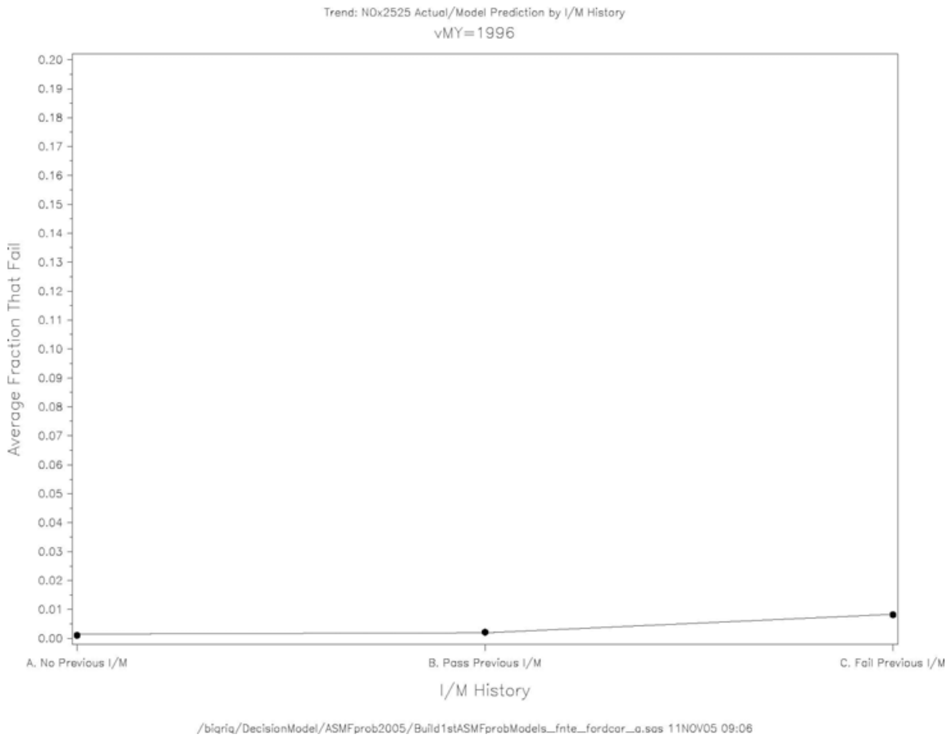

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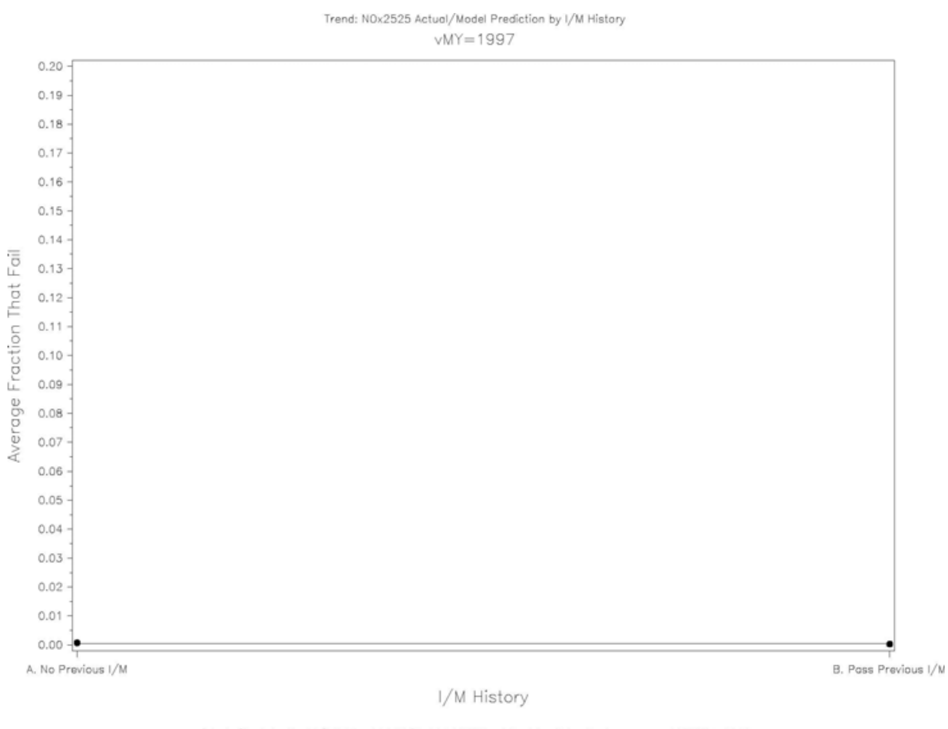

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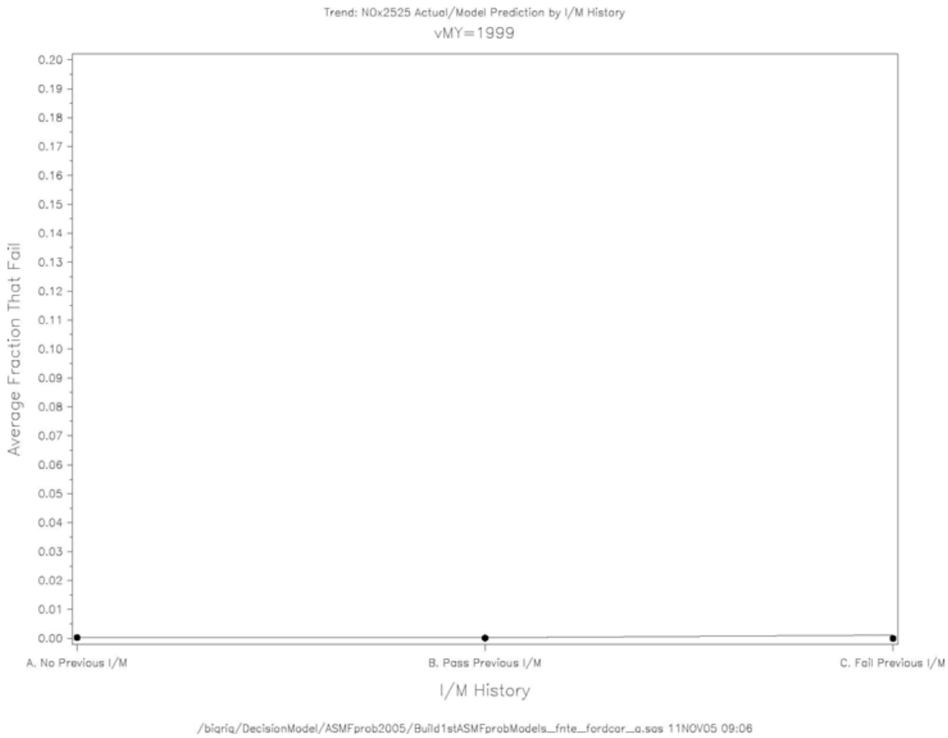

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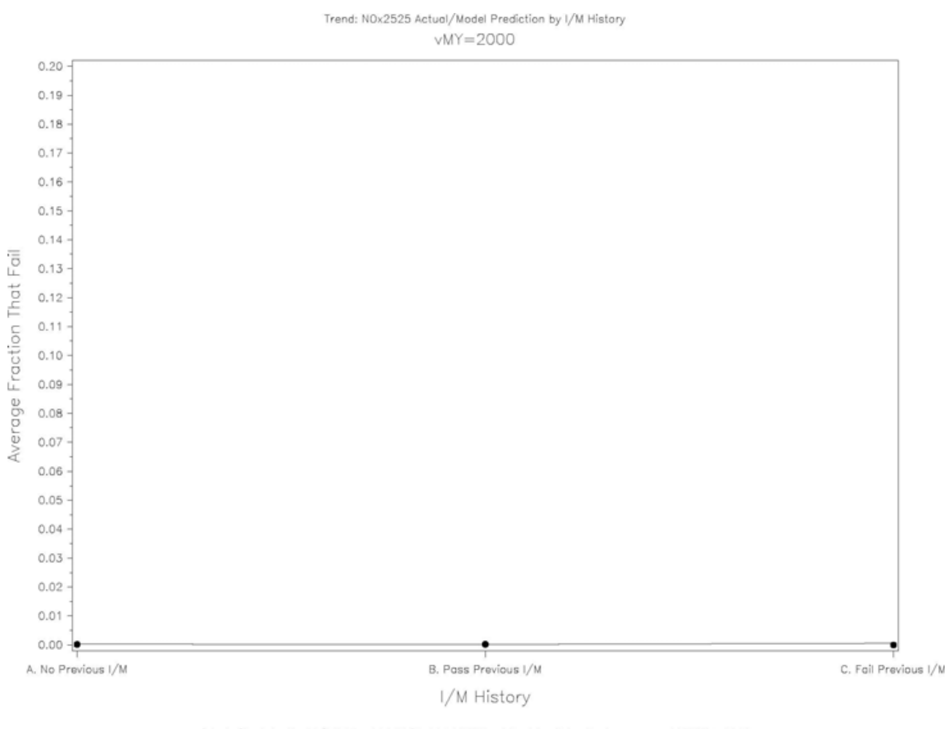

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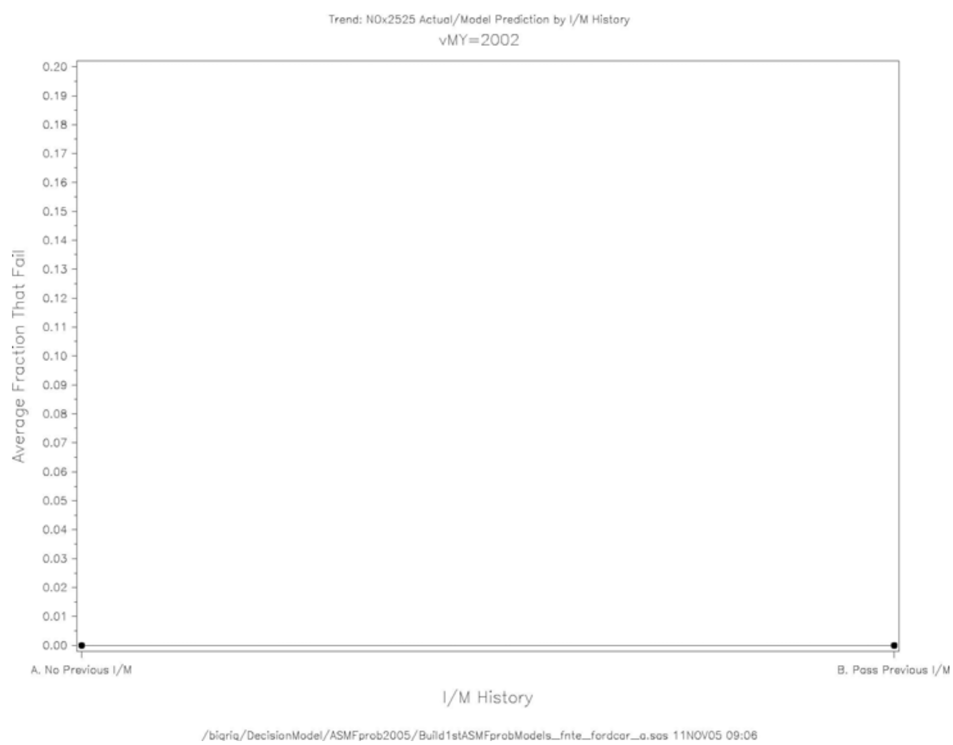
Figure M-64.



Appendix N

2004 Estimated Annual Average Emissions and Statewide Vehicle Population

Table N-1. EMFAC Run for the Default Biennial I/M Program Case

2004 Estimated Summer Average Emissions and Statewide Vehicle Populations

English tons/day	TOG_TOTEX Default Biennial IM Case				
Model Year	**LDA**	**LDT1**	**LDT2**	**MDV**	
1965	6.893	5.019	0.192	0.418	
1966	2.443	0.791	0.450	0.098	
1967	2.559	0.835	0.449	0.111	
1968	2.829	1.105	0.683	0.134	
1969	3.464	1.443	1.117	0.221	
1970	3.493	1.820	1.247	0.282	
1971	3.611	2.015	1.291	0.502	
1972	4.831	3.342	2.010	0.630	
1973	5.479	3.432	2.350	0.706	
1974	3.307	1.899	1.641	0.333	
1975	1.019	1.820	1.444	0.327	
1976	1.606	1.037	0.792	0.941	
1977	1.858	1.432	1.202	1.446	
1978	2.544	1.672	1.140	0.464	
1979	3.000	1.229	1.095	0.523	
1980	1.756	1.042	0.578	0.407	
1981	1.884	1.021	0.583	0.421	
1982	2.479	1.222	0.528	0.510	
1983	3.335	0.986	0.409	0.813	
1984	5.238	1.886	0.888	1.581	
1985	5.343	2.027	1.213	1.073	
1986	6.306	3.070	1.678	1.160	
1987	8.265	2.844	1.755	1.408	
1988	9.827	3.201	1.992	1.355	
1989	12.835	3.646	2.726	1.779	
1990	14.120	3.144	3.021	1.476	
1991	15.226	3.393	3.600	1.567	
1992	13.882	3.108	3.940	1.293	
1993	13.181	2.871	4.076	2.133	
1994	9.626	2.739	3.281	1.949	
1995	9.149	2.092	3.536	1.973	
1996	6.541	1.652	2.473	1.533	
1997	6.420	1.839	2.634	1.643	
1998	4.793	1.223	2.243	1.351	
1999	3.764	0.810	1.881	1.487	
2000	2.544	0.589	1.231	1.050	
2001	2.326	0.553	1.065	0.768	
2002	2.331	0.555	0.967	0.706	
2003	2.175	0.524	0.906	0.629	
2004	1.762	0.441	0.315	0.230	
Total	214.044	75.367	64.624	37.429	391.5

English tons/day	CO Default Biennial IM Case				
Model Year	**LDA**	**LDT1**	**LDT2**	**MDV**	
1965	71.762	53.575	2.039	4.434	
1966	27.714	9.230	5.252	1.169	
1967	29.080	9.759	5.238	1.324	
1968	32.233	12.916	7.965	1.599	
1969	39.535	16.878	13.053	2.642	
1970	40.305	21.555	14.737	3.371	
1971	40.285	22.835	14.582	5.992	
1972	52.530	36.355	21.795	7.366	
1973	58.854	36.748	25.096	8.272	
1974	34.535	19.503	16.778	4.238	
1975	14.781	20.668	16.353	3.893	
1976	23.395	28.612	21.866	17.478	
1977	32.514	39.592	33.251	26.202	
1978	45.057	46.249	31.526	12.826	
1979	52.417	25.522	18.597	14.433	
1980	33.677	20.545	9.345	10.252	
1981	33.244	20.257	9.491	6.089	
1982	43.959	25.304	8.979	7.379	
1983	59.273	24.446	8.351	11.805	
1984	93.893	45.673	17.684	30.020	
1985	82.347	47.676	23.461	15.744	
1986	88.290	71.903	32.304	15.879	
1987	113.515	65.248	33.044	18.395	
1988	132.444	69.283	35.446	18.147	
1989	189.642	79.255	48.685	24.321	
1990	222.140	66.163	52.102	19.267	
1991	238.655	67.335	58.609	20.493	
1992	217.230	60.503	62.995	16.709	
1993	195.397	42.204	60.515	27.109	
1994	131.841	37.122	45.025	25.203	
1995	118.172	27.192	46.661	24.115	
1996	91.646	25.676	38.853	22.426	
1997	101.251	31.798	45.684	24.742	
1998	91.971	24.972	45.848	22.001	
1999	90.514	19.963	45.698	25.181	
2000	79.834	18.511	37.358	18.459	
2001	71.003	16.929	31.534	13.982	
2002	69.521	16.645	28.141	12.977	
2003	64.883	15.794	26.306	13.733	
2004	54.458	13.848	9.547	4.999	
Total	3303.795	1354.243	1109.793	564.669	6332.5

English tons/day	NOX Default Biennial IM Case				
Model Year	**LDA**	**LDT1**	**LDT2**	**MDV**	
1965	4.096	3.123	0.118	0.258	
1966	1.655	0.564	0.321	0.071	
1967	1.736	0.598	0.320	0.080	
1968	1.925	0.791	0.486	0.097	
1969	2.363	1.034	0.797	0.161	
1970	2.405	1.318	0.897	0.205	
1971	2.434	1.412	0.899	0.364	
1972	3.189	2.274	1.361	0.450	
1973	3.593	2.312	1.577	0.506	
1974	2.024	1.177	1.012	0.255	
1975	1.104	0.930	0.735	0.236	
1976	1.737	1.186	0.906	0.912	
1977	1.890	1.641	1.372	1.364	
1978	2.592	1.915	1.299	0.607	
1979	3.122	1.443	1.404	0.686	
1980	2.172	1.256	0.761	0.536	
1981	2.278	0.997	0.702	0.424	
1982	3.060	1.388	0.740	0.519	
1983	4.237	2.251	0.768	0.735	
1984	7.113	4.090	1.581	2.006	
1985	8.749	5.179	2.537	2.447	
1986	10.593	8.045	3.599	2.642	
1987	13.891	7.571	3.819	3.169	
1988	16.479	8.582	4.370	3.076	
1989	17.362	6.859	5.989	3.987	
1990	15.838	4.102	6.569	3.333	
1991	17.153	4.355	7.700	3.538	
1992	15.704	3.975	8.405	2.927	
1993	16.332	4.332	9.806	4.865	
1994	13.619	4.117	9.404	4.560	
1995	14.634	3.557	8.219	4.944	
1996	11.985	3.020	6.200	4.006	
1997	11.728	3.366	6.653	4.392	
1998	9.772	2.463	6.440	3.794	
1999	8.523	1.815	6.134	4.226	
2000	6.407	1.491	4.649	2.943	
2001	5.974	1.432	4.116	1.999	
2002	5.961	1.436	3.743	1.825	
2003	5.526	1.354	3.416	1.684	
2004	4.127	1.057	1.106	0.760	
Total	285.084	109.807	130.932	75.589	601.4

	Populations Vehicles				
Model Year	**LDA**	**LDT1**	**LDT2**	**MDV**	
1965	62,897	32,271	1,214	2,641	
1966	24,850	6,054	3,375	749	
1967	25,431	6,247	3,309	840	
1968	27,237	8,160	5,016	990	
1969	32,379	10,469	8,000	1,634	
1970	31,721	13,089	8,927	2,051	
1971	31,275	13,987	8,834	3,552	
1972	39,899	22,412	13,189	4,364	
1973	43,447	22,471	14,834	4,765	
1974	27,850	13,149	11,006	2,678	
1975	18,402	11,698	8,916	2,506	
1976	27,951	16,188	11,963	3,550	
1977	39,829	21,808	17,807	5,204	
1978	53,010	24,865	16,467	6,752	
1979	60,531	26,426	18,791	7,478	
1980	48,880	21,586	9,616	5,442	
1981	59,525	23,372	10,748	6,185	
1982	75,616	30,170	10,490	7,324	
1983	103,321	35,622	11,904	13,459	
1984	175,878	64,541	24,550	26,383	
1985	233,444	79,491	38,557	35,309	
1986	290,458	121,876	54,054	38,986	
1987	374,498	113,537	57,073	46,928	
1988	434,422	130,967	66,472	44,400	
1989	526,673	147,375	89,870	56,513	
1990	543,689	125,956	98,950	47,543	
1991	578,151	135,300	117,306	49,803	
1992	518,306	122,743	127,642	41,042	
1993	582,256	141,818	158,056	68,503	
1994	628,000	179,639	169,390	63,817	
1995	743,920	161,004	214,661	80,008	
1996	661,918	155,319	182,841	83,407	
1997	741,366	196,325	220,073	91,932	
1998	731,448	175,226	252,752	93,823	
1999	787,670	162,016	293,161	124,818	
2000	768,534	179,690	288,544	111,084	
2001	771,327	184,919	273,207	106,285	
2002	817,471	193,501	260,897	101,685	
2003	881,734	207,562	248,666	97,699	
2004	922,462	218,828	245,706	101,334	
Total	13,547,674	3,557,676	3,676,833	1,593,467	**22,375,650**

	VMT Miles per Day				
Model Year	**LDA**	**LDT1**	**LDT2**	**MDV**	
1965	734,345	577,820	22,018	6,605	
1966	314,391	110,849	63,314	2,395	
1967	330,266	117,398	63,161	4,260	
1968	367,053	155,327	96,001	6,051	
1969	451,470	203,196	157,626	13,253	
1970	459,653	258,224	176,953	21,249	
1971	469,522	278,772	178,667	36,684	
1972	618,001	452,266	272,283	65,616	
1973	699,708	461,253	316,726	110,503	
1974	463,777	277,056	239,670	46,866	
1975	317,415	247,676	197,525	62,056	
1976	498,654	347,205	267,567	119,793	
1977	737,443	477,676	404,189	156,842	
1978	1,015,202	556,759	382,451	179,029	
1979	1,200,294	606,012	445,978	136,656	
1980	1,001,614	506,442	232,241	38,224	
1981	1,264,438	562,890	265,386	59,766	
1982	1,661,762	741,164	264,840	80,412	
1983	2,340,046	884,983	303,239	115,838	
1984	4,119,488	1,637,777	635,567	190,870	
1985	5,653,185	2,065,117	1,015,295	145,118	
1986	7,262,352	3,221,969	1,446,465	115,146	
1987	9,695,452	3,076,596	1,557,211	122,762	
1988	11,638,371	3,632,106	1,853,577	131,089	
1989	14,594,246	4,167,689	2,555,251	135,264	
1990	15,551,817	3,645,778	2,867,686	111,495	
1991	17,068,930	4,007,682	3,481,608	84,349	
1992	15,851,989	3,733,054	3,877,174	86,009	
1993	18,426,046	4,431,012	4,927,808	68,012	
1994	20,577,452	5,777,352	5,421,536	88,849	
1995	25,216,498	5,337,910	7,060,866	94,737	
1996	23,215,020	5,303,066	6,190,103	76,992	
1997	26,885,258	6,930,490	7,676,920	82,312	
1998	27,410,996	6,399,874	9,097,663	73,712	
1999	30,508,116	6,127,424	10,913,851	118,017	
2000	30,896,272	7,092,915	11,163,109	137,492	
2001	32,240,682	7,675,312	11,019,172	152,101	
2002	35,442,988	8,498,427	11,043,040	170,443	
2003	39,608,912	9,721,030	11,162,716	194,837	
2004	42,928,832	11,139,335	11,930,936	219,762	
Total	469,737,950	121,444,870	131,247,380	3,861,467	**726,291,667**

	TOG LDA	TOG LDT1	TOG LDT2	TOG MDV	**Total**	CO LDA	CO LDT1	CO LDT2	CO MDV	**Total**	NOX LDA	NOX LDT1	NOX LDT2	NOX MDV	**Total**	Pop. LDA	Pop. LDT1	Pop. LDT2	Pop. MDV	**Total**	VMT LDA	VMT LDT1	VMT LDT2	VMT MDV	**Total**
1976 - 2004	174.1	51.8	51.8	33.7	311.4	2862	1094	967	520	5444	258.6	94.3	122.4	72.9	548.1	13,182,290	3,397,669	3,590,213	1,566,697	21,736,869	464,512,356	118,305,045	129,463,443	3,485,928	715,766,772
1976 - 1998	159.2	48.4	45.4	28.8	$\boxed{281.8}$	2432	993	788	431	$\boxed{4644}$	222.0	85.7	99.2	59.5	$\boxed{466.4}$	8,233,091	2,251,154	1,980,033	923,791	$\boxed{13,388,069}$	252,886,554	68,050,602	62,230,619	2,493,276	$\boxed{385,661,051}$

Source: "Fleet_Emission_Count_Summary.xls" - Data from an EMFAC run by ERG (Mark Hebets) on 02/20/2006 (proj1/DecisionModel/Report/StAvg2004_ExhaustTOGbyModelYear_appN_2tabs.xls)

2006/2/20 Runs with version 2.20.8

Title : Statewide totals Avg Summer CYr 2004
Version : Emfac2007 working draft V2.20 Feb 10 2005
Run Date : 2/20/2006 11:26
Scen Year: 2004 -- All model years in the range 1965 to 2004 selected
Season : Summer
Area : Statewide totals
I/M Stat : I and M program in effect
Emissions: English Tons Per Period

Table N-2. EMFAC Run for the No-I/M Case

2004 Estimated Summer Average Emissions and Statewide Vehicle Populations

English tons/day

Model Year	TOG_TOTEX No-IM Case LDA	LDT1	LDT2	MDV	
1965	6.893	5.019	0.192	0.418	
1966	2.920	0.965	0.552	0.121	
1967	3.050	1.015	0.548	0.137	
1968	3.362	1.338	0.831	0.165	
1969	4.103	1.740	1.355	0.271	
1970	4.138	2.197	1.513	0.344	
1971	4.205	2.375	1.527	0.609	
1972	5.534	3.854	2.324	0.753	
1973	6.227	3.919	2.688	0.842	
1974	4.108	2.344	2.028	0.483	
1975	1.236	2.201	1.748	0.459	
1976	1.962	1.275	0.977	1.244	
1977	3.578	1.759	1.481	1.863	
1978	4.899	2.049	1.401	0.571	
1979	5.505	2.433	2.170	0.642	
1980	2.956	2.098	1.168	0.542	
1981	4.218	1.894	1.085	0.845	
1982	5.534	2.117	0.919	1.021	
1983	7.389	1.636	0.682	1.464	
1984	12.026	3.174	1.499	3.380	
1985	8.424	3.292	1.974	1.652	
1986	9.127	4.900	2.683	1.704	
1987	11.863	4.443	2.748	2.026	
1988	13.931	4.832	3.014	1.960	
1989	18.488	5.485	4.109	2.604	
1990	20.589	4.663	4.487	2.099	
1991	22.126	4.926	5.231	2.223	
1992	20.106	4.469	5.679	1.825	
1993	18.292	3.973	5.604	2.879	
1994	12.349	3.634	4.326	2.545	
1995	11.023	2.679	4.499	2.500	
1996	8.013	2.138	3.153	1.992	
1997	7.502	2.257	3.174	2.005	
1998	5.439	1.437	2.610	1.586	
1999	4.034	0.881	2.028	1.610	
2000	2.546	0.592	1.232	1.052	
2001	2.316	0.551	1.061	0.765	
2002	2.331	0.555	0.967	0.706	
2003	2.175	0.524	0.906	0.629	
2004	1.762	0.441	0.315	0.230	
Total	296.281	102.076	86.486	50.764	535.6

Model Year	CO No-IM Case LDA	LDT1	LDT2	MDV	
1965	71.762	53.575	2.039	4.434	
1966	30.209	10.168	5.795	1.290	
1967	31.638	10.733	5.766	1.457	
1968	35.009	14.170	8.752	1.757	
1969	42.885	18.484	14.316	2.898	
1970	43.671	23.543	16.121	3.687	
1971	43.503	24.833	15.888	6.539	
1972	56.482	39.362	23.639	8.007	
1973	63.144	39.669	27.131	8.971	
1974	41.363	23.505	20.262	5.155	
1975	19.543	26.562	21.051	4.819	
1976	30.992	38.353	29.350	21.502	
1977	47.238	52.987	44.560	32.099	
1978	65.235	61.797	42.180	17.150	
1979	75.211	37.030	27.098	19.267	
1980	46.765	30.130	13.750	13.753	
1981	59.204	28.971	13.621	8.990	
1982	78.074	35.564	12.681	10.874	
1983	105.278	34.218	11.708	16.901	
1984	173.630	63.617	24.664	43.892	
1985	122.343	65.457	32.178	22.173	
1986	117.145	97.612	43.820	21.227	
1987	149.521	87.326	44.237	24.300	
1988	172.743	91.348	46.656	23.905	
1989	244.412	103.734	63.627	31.995	
1990	284.166	85.602	67.382	24.893	
1991	303.611	86.174	74.843	26.258	
1992	273.950	76.501	79.432	21.104	
1993	244.610	52.938	75.751	33.722	
1994	165.868	46.412	56.180	30.769	
1995	147.899	33.649	57.521	28.979	
1996	109.234	30.792	46.218	27.151	
1997	115.044	36.494	51.964	28.509	
1998	100.966	27.622	50.385	24.430	
1999	94.907	20.999	47.859	26.467	
2000	78.591	18.314	36.783	18.211	
2001	70.203	16.748	31.182	13.825	
2002	69.521	16.645	28.141	12.977	
2003	64.883	15.794	26.306	13.733	
2004	54.458	13.848	9.547	4.999	
Total	4144.910	1691.277	1350.385	693.069	7879.6

Model Year	NOX No-IM Case LDA	LDT1	LDT2	MDV	
1965	4.0963	3.1227	0.1185	0.2578	
1966	1.7324	0.5943	0.3377	0.0751	
1967	1.8168	0.6284	0.3365	0.0849	
1968	2.0137	0.8307	0.5114	0.1025	
1969	2.4707	1.0853	0.8380	0.1693	
1970	2.5172	1.3828	0.9438	0.2157	
1971	2.5260	1.4679	0.9364	0.3832	
1972	3.2811	2.3426	1.4030	0.4709	
1973	3.6842	2.3712	1.6179	0.5285	
1974	2.4220	1.4122	1.2144	0.3041	
1975	1.6114	1.2334	0.9775	0.2859	
1976	2.5385	1.7417	1.3347	1.1068	
1977	2.4699	2.4002	2.0200	1.6563	
1978	3.4098	2.7983	1.9118	0.8932	
1979	4.1691	1.9220	1.8766	1.0051	
1980	3.1285	1.6869	1.0265	0.7884	
1981	3.6547	1.4467	1.0195	0.5606	
1982	4.8242	2.0746	1.1081	0.6919	
1983	6.6165	3.4759	1.1872	1.0535	
1984	11.4963	6.2511	2.4186	2.9766	
1985	13.0018	7.9648	3.9069	3.8514	
1986	16.5194	12.2587	5.4910	4.1889	
1987	21.5125	11.5260	5.8233	4.9493	
1988	25.2869	13.0612	6.6547	4.8144	
1989	26.0785	10.3341	9.0080	6.1616	
1990	23.1773	6.0700	9.6935	5.0316	
1991	24.4743	6.2681	11.0132	5.2203	
1992	21.6759	5.5231	11.5985	4.1439	
1993	21.6933	5.8090	13.0579	6.5843	
1994	17.1551	5.3531	12.1211	5.9239	
1995	17.7012	4.4731	10.2624	6.1816	
1996	14.4299	3.7253	7.5298	4.9122	
1997	13.5538	3.9812	7.8026	5.1863	
1998	10.9987	2.8508	7.3488	4.3251	
1999	9.1702	1.9824	6.6184	4.5530	
2000	6.4580	1.5124	4.6892	2.9809	
2001	5.9534	1.4293	4.1032	1.9924	
2002	5.9614	1.4362	3.7427	1.8250	
2003	5.5255	1.3539	3.4161	1.6835	
2004	4.1273	1.0575	1.1063	0.7600	
Total	374.9337	148.2390	168.1258	98.8795	790.2

Model Year	Populations Vehicles LDA	LDT1	LDT2	MDV	
1965	62,897	32,271	1,214	2,641	
1966	24,850	6,054	3,375	749	
1967	25,431	6,247	3,309	840	
1968	27,237	8,160	5,016	990	
1969	32,379	10,469	8,000	1,634	
1970	31,721	13,089	8,927	2,051	
1971	31,275	13,987	8,834	3,552	
1972	39,899	22,412	13,189	4,364	
1973	43,447	22,471	14,834	4,765	
1974	27,850	13,149	11,006	2,678	
1975	18,402	11,698	8,916	2,506	
1976	27,951	16,188	11,963	3,550	
1977	39,829	21,808	17,807	5,204	
1978	53,010	24,865	16,467	6,752	
1979	60,531	26,426	18,791	7,478	
1980	48,880	21,586	9,616	5,442	
1981	59,525	23,372	10,748	6,185	
1982	75,616	30,170	10,490	7,324	
1983	103,321	35,622	11,904	13,459	
1984	175,878	64,541	24,550	26,383	
1985	233,444	79,491	38,557	35,309	
1986	290,458	121,876	54,054	38,986	
1987	374,498	113,537	57,073	46,928	
1988	434,422	130,967	66,472	44,400	
1989	526,673	147,375	89,870	56,513	
1990	543,689	125,956	98,950	47,543	
1991	578,151	135,300	117,306	49,803	
1992	518,306	122,743	127,642	41,042	
1993	582,256	141,818	158,056	68,503	
1994	628,000	179,639	169,390	63,817	
1995	743,920	161,004	214,661	80,008	
1996	661,918	155,319	182,841	83,407	
1997	741,366	196,325	220,073	91,932	
1998	731,448	175,226	252,752	93,823	
1999	787,670	162,016	293,161	124,818	
2000	768,534	179,690	288,544	111,084	
2001	771,327	184,919	273,207	106,285	
2002	817,471	193,501	260,897	101,685	
2003	881,734	207,562	248,666	97,699	
2004	922,462	218,828	245,706	101,334	
Total	13,547,674	3,557,676	3,676,833	1,593,467	**22,375,650**

Model Year	VMT Miles per Day LDA	LDT1	LDT2	MDV	
1965	734,345	577,820	22,018	6,605	
1966	314,391	110,849	63,314	2,395	
1967	330,266	117,398	63,161	4,260	
1968	367,053	155,327	96,001	6,051	
1969	451,470	203,196	157,626	13,253	
1970	459,653	258,224	176,953	21,249	
1971	469,522	278,772	178,667	36,684	
1972	618,001	452,266	272,283	65,616	
1973	699,708	461,253	316,726	110,503	
1974	463,777	277,056	239,670	46,866	
1975	317,415	247,676	197,525	62,056	
1976	498,654	347,205	267,567	119,793	
1977	737,443	477,676	404,189	156,842	
1978	1,015,202	556,759	382,451	179,029	
1979	1,200,294	606,012	445,978	136,656	
1980	1,001,614	506,442	232,241	38,224	
1981	1,264,438	562,890	265,386	59,766	
1982	1,661,762	741,164	264,840	80,412	
1983	2,340,046	884,983	303,239	115,838	
1984	4,119,488	1,637,777	635,567	190,870	
1985	5,653,185	2,065,117	1,015,295	145,118	
1986	7,262,352	3,221,969	1,446,465	115,146	
1987	9,695,452	3,076,596	1,557,211	122,762	
1988	11,638,371	3,632,106	1,853,577	131,089	
1989	14,594,246	4,167,689	2,555,251	135,264	
1990	15,551,817	3,645,778	2,867,686	111,495	
1991	17,068,930	4,007,682	3,481,608	84,349	
1992	15,851,989	3,733,054	3,877,174	86,009	
1993	18,426,046	4,431,012	4,927,808	68,012	
1994	20,577,452	5,777,352	5,421,536	88,849	
1995	25,216,498	5,337,910	7,060,866	94,737	
1996	23,215,020	5,303,066	6,190,103	76,992	
1997	26,885,258	6,930,490	7,676,920	82,312	
1998	27,410,996	6,399,874	9,097,663	73,712	
1999	30,508,116	6,127,424	10,913,851	118,017	
2000	30,896,272	7,092,915	11,163,109	137,492	
2001	32,240,682	7,675,312	11,019,172	152,101	
2002	35,442,988	8,498,427	11,043,040	170,443	
2003	39,608,912	9,721,030	11,162,716	194,837	
2004	42,928,832	11,139,335	11,930,936	219,762	
Total	469,737,950	121,444,870	131,247,380	3,861,467	**726,291,667**

	TOG LDA	TOG LDT1	TOG LDT2	TOG MDV	Total	CO LDA	CO LDT1	CO LDT2	CO MDV	Total	NOX LDA	NOX LDT1	NOX LDT2	NOX MDV	Total	Pop LDA	Pop LDT1	Pop LDT2	Pop MDV	Total	VMT LDA	VMT LDT1	VMT LDT2	VMT MDV	Total
1976 - 2004	250.5	75.1	71.2	46.2	443.0	3665.702	1406.673	1189.625	644.0558	6906	346.8	131.8	158.9	96.0	733.4	13,182,290	3,397,669	3,590,213	1,566,697	21,736,869	464,512,356	118,305,045	129,463,443	3,485,928	715,766,772
1976 - 1998	235.3	71.6	64.7	41.2	**412.7**	3233.139	1304.326	1009.808	553.8426	**6101**	309.6	123.0	135.2	82.2	**650.0**	8,233,091	2,251,154	1,980,033	923,791	**13,388,069**	252,886,554	68,050,602	62,230,619	2,493,276	**385,661,051**

Source: "Fleet_Emission_Count_Summary.xls" - Data from an EMFAC run by ERG (Mark Hebets) on 02/20/2006 (proj1/DecisionModel/Report/StAvg2004_ExhaustTOGbyModelYear_appN_2tabs.xls)

2006/2/20 Runs with version 2.20.8

# Title :	Statewide totals Avg Summer CYr 2004
# Version :	Emfac2007 working draft V2.20 Feb 10 2005
# Run Date :	2/20/2006 11:26
# Scen Year:	2004 -- All model years in the range 1965 to 2004 selected
# Season :	Summer
# Area :	Statewide totals
# I/M Stat :	I and M program **NOT** in effect since 1984
# Emissions:	English Tons Per Period

Appendix O

Performance Evaluation Plots Using Model C as the Reference

To facilitate comparisons with figures in the body of the report, Appendix O figure labels begin with Figure O-4.

Figure O-4. Change in Failed Miles Driven Over 24 Months vs. Percent Fleet Targeting for Directing (Truth ≈ Model C)

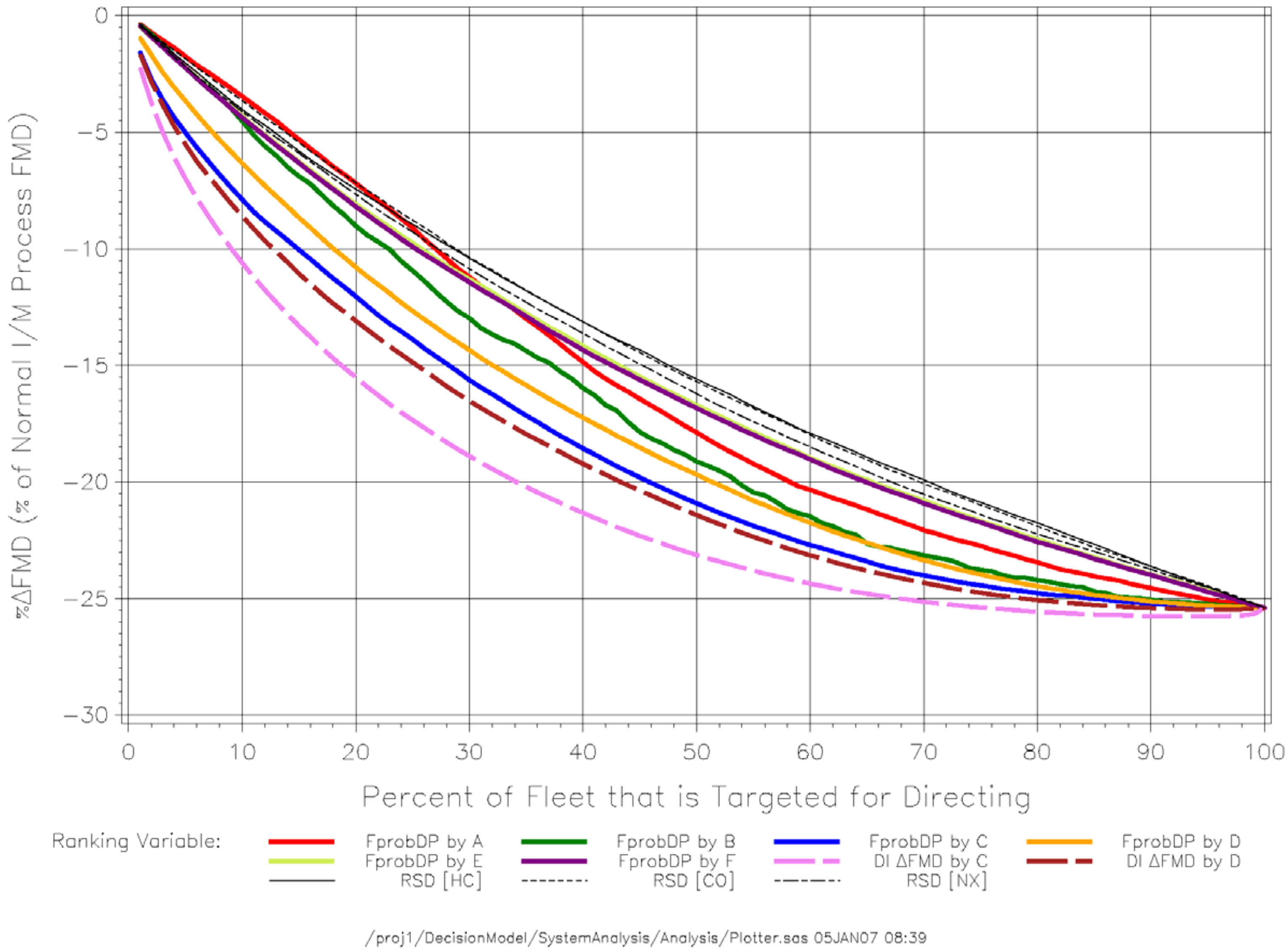


Figure O-5. Change in FTP HC Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Directing (Truth ≈ Model C)

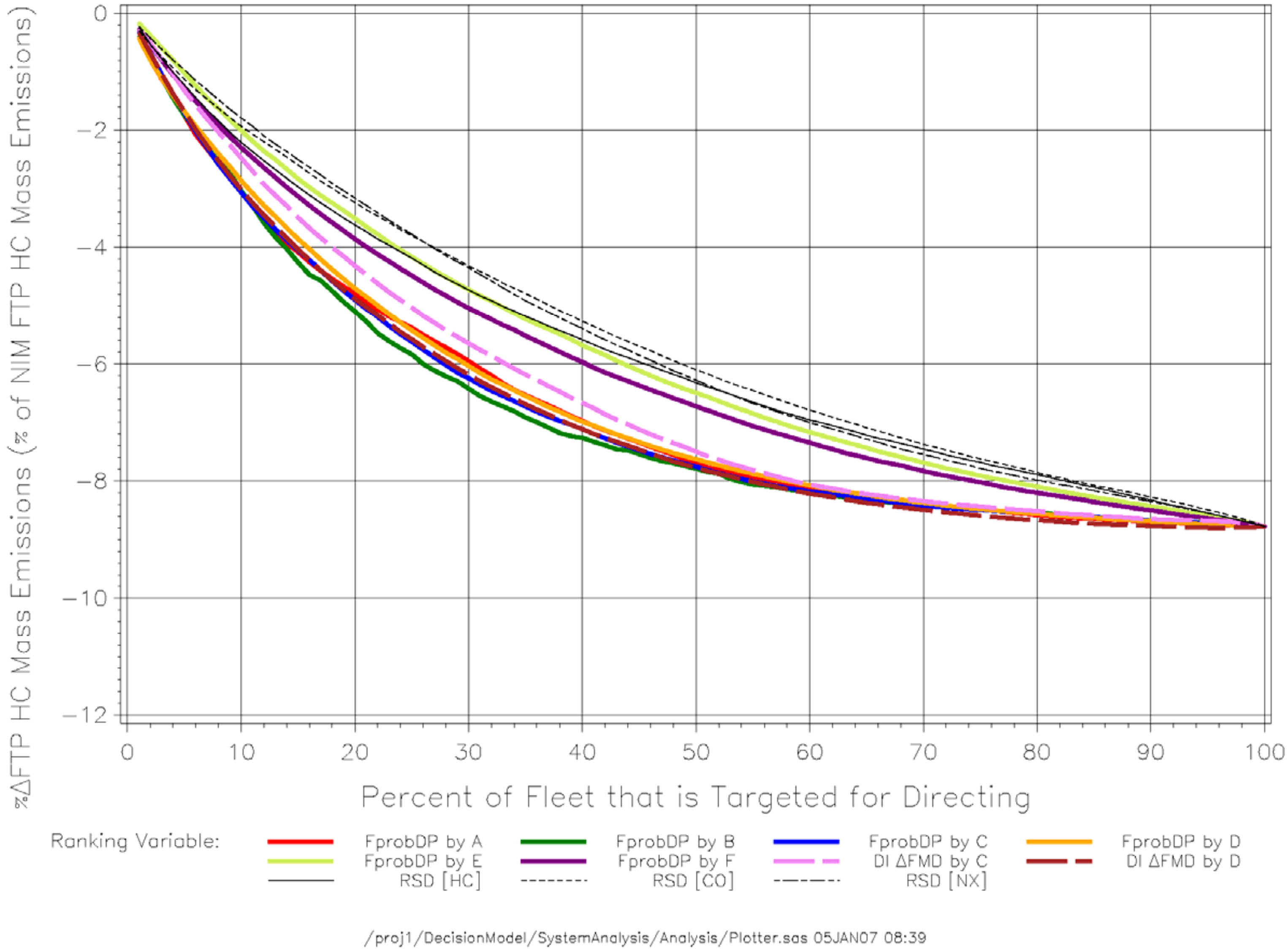


Figure O-6. Change in FTP CO Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Directing (Truth ≈ Model C)

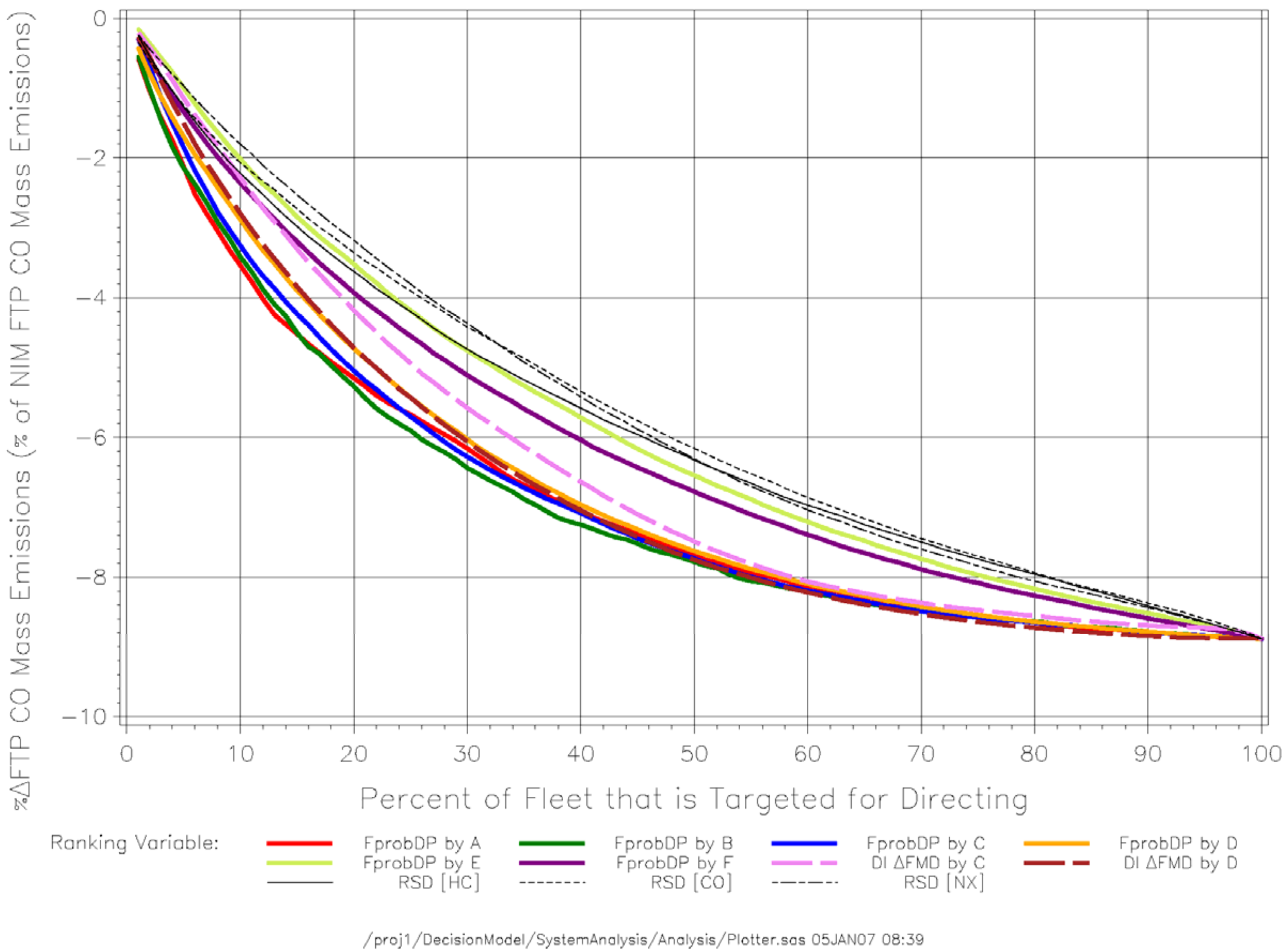


Figure O-7. Change in FTP NX Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Directing (Truth ≈ Model C)

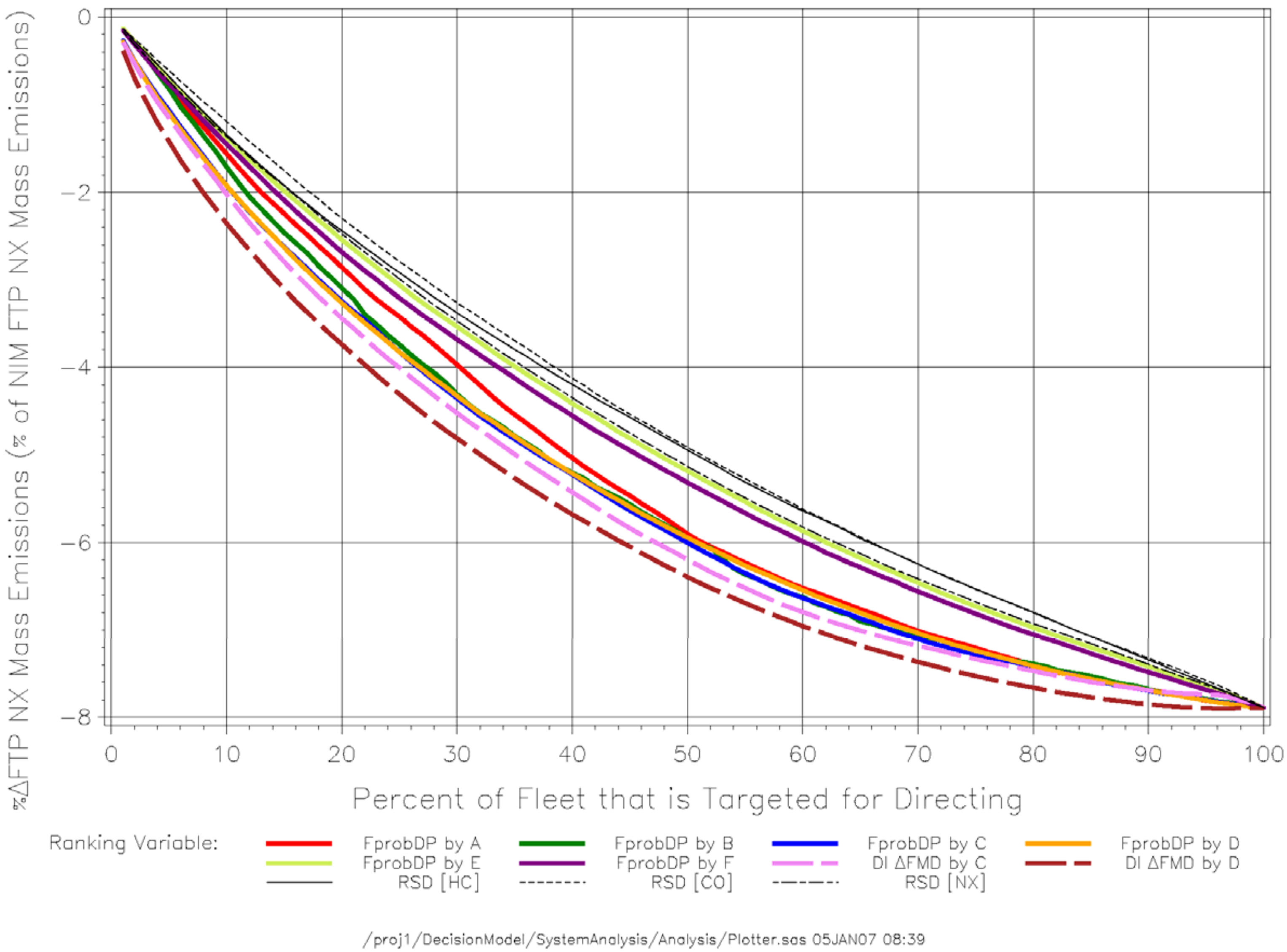


Figure O-8. Fail Fraction of Targeted Vehicles at the Decision Point vs. Percent Fleet Targeting for Directing (Truth ≈ Model C)

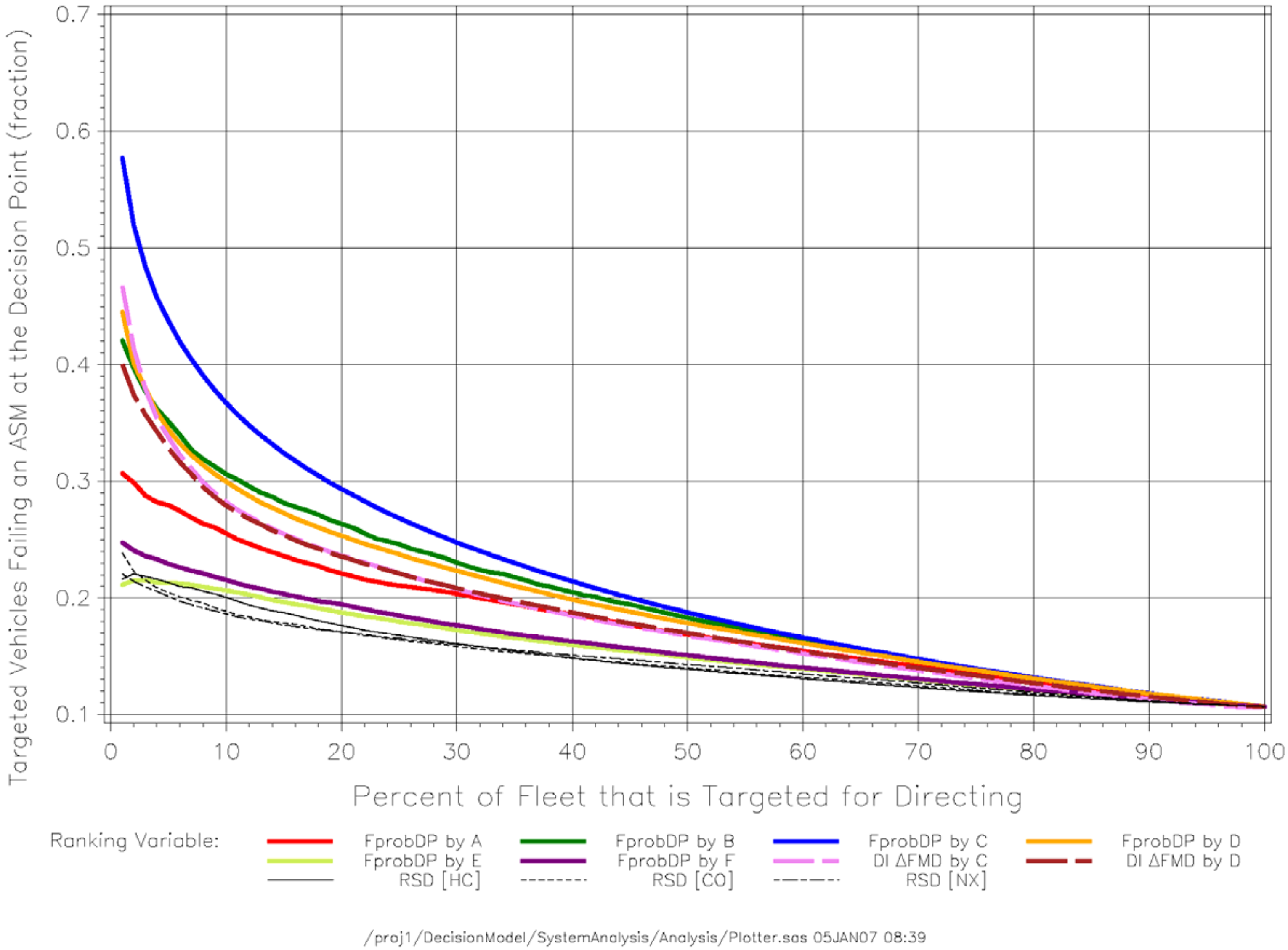


Figure O-9. Change in Failed Miles Driven Over 24 Months vs. Percent Fleet Targeting for Exempting (Truth ≈ Model C)

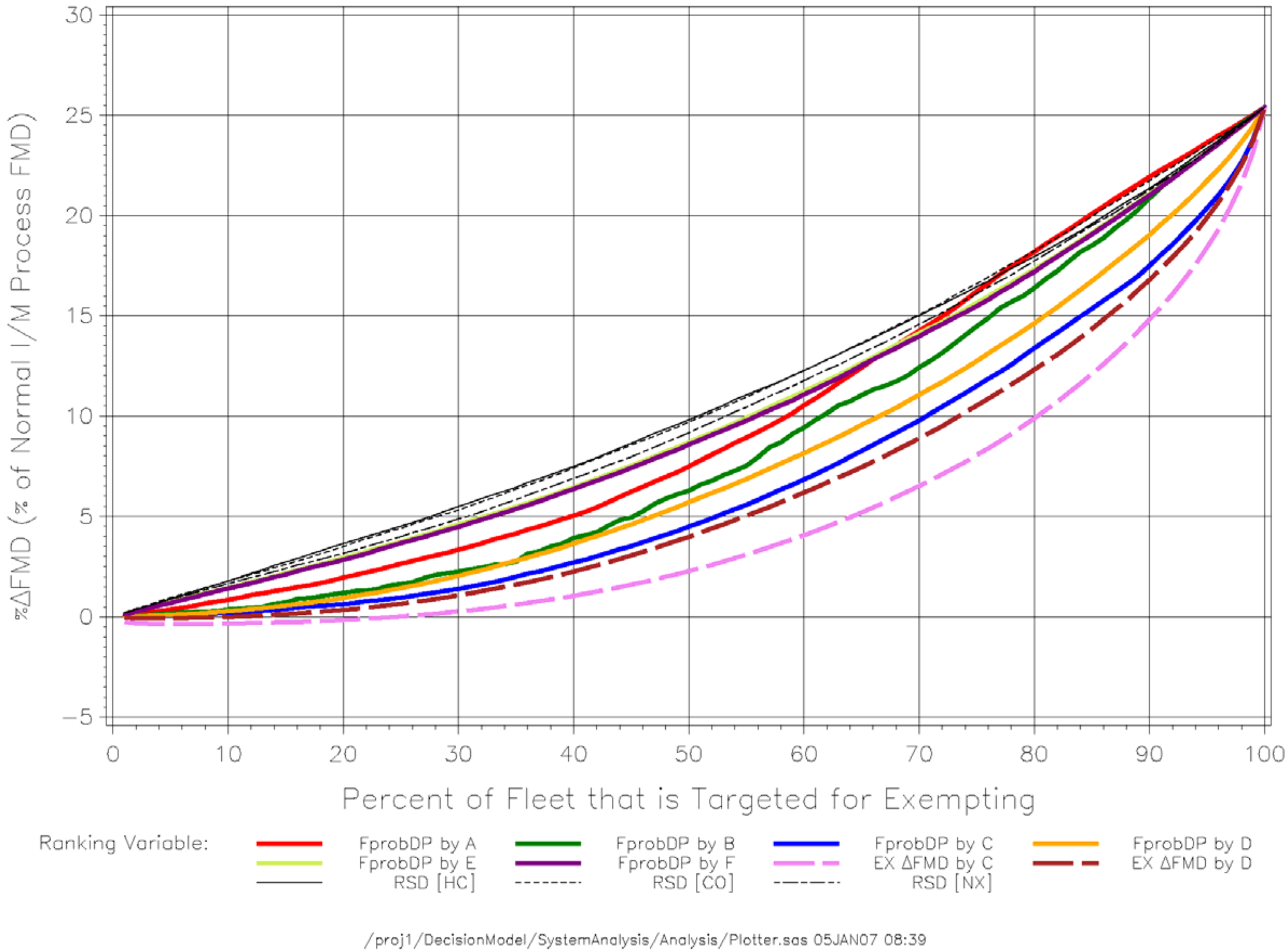


Figure O-10. Change in FTP HC Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Exempting (Truth ≈ Model C)

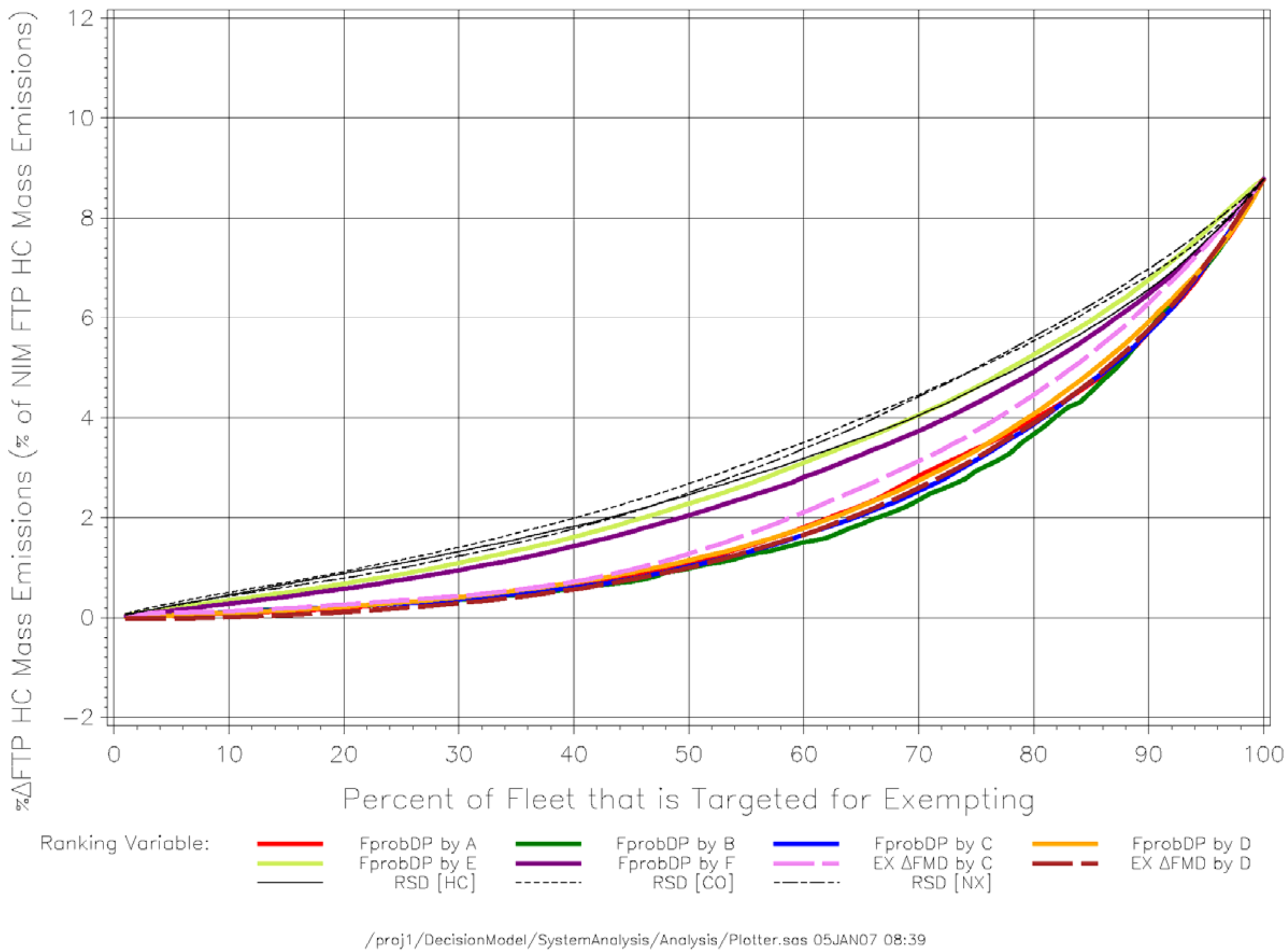


Figure O-11. Change in FTP CO Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Exempting (Truth ≈ Model C)

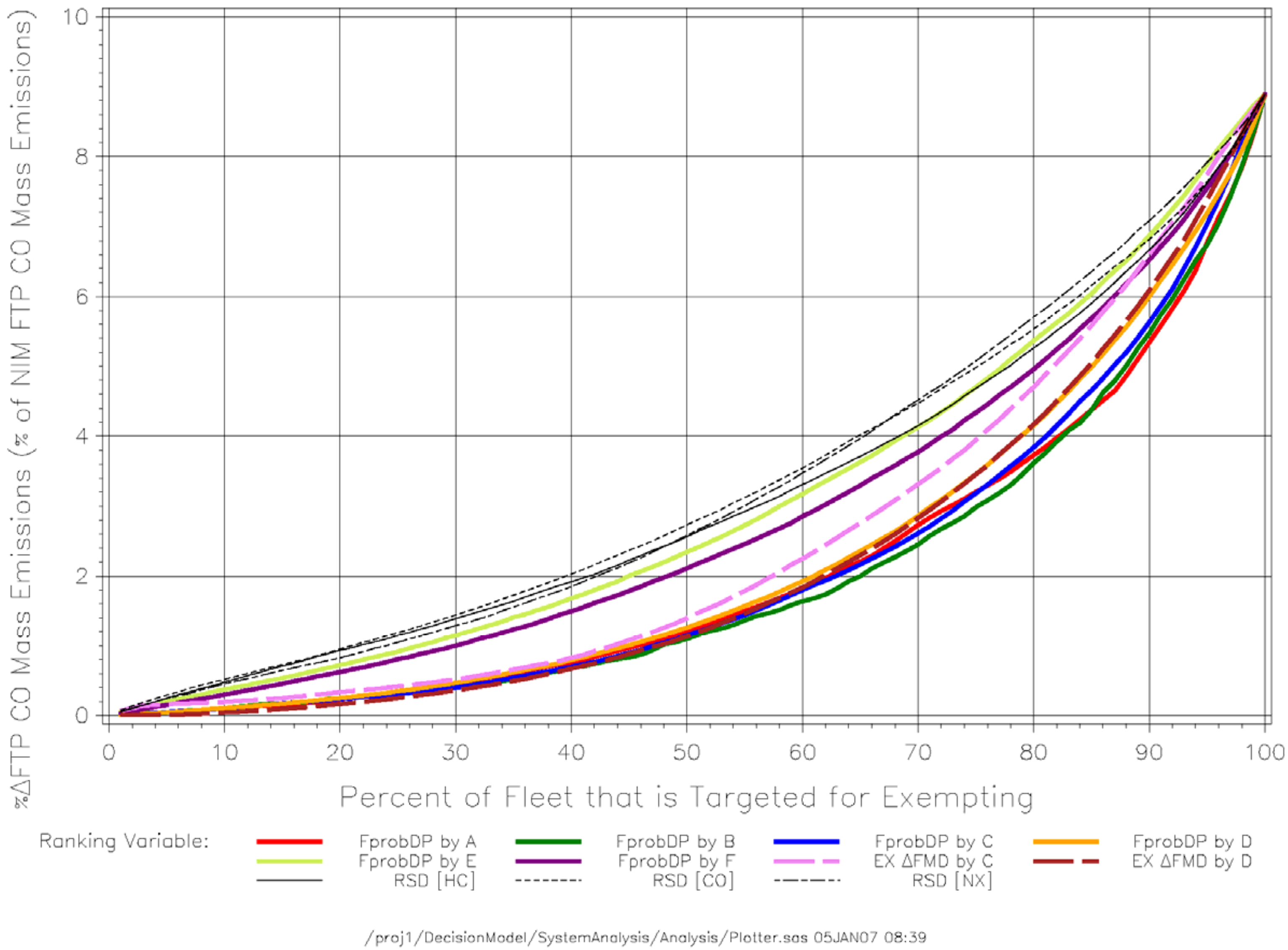


Figure O-12. Change in FTP NX Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Exempting (Truth ≈ Model C)

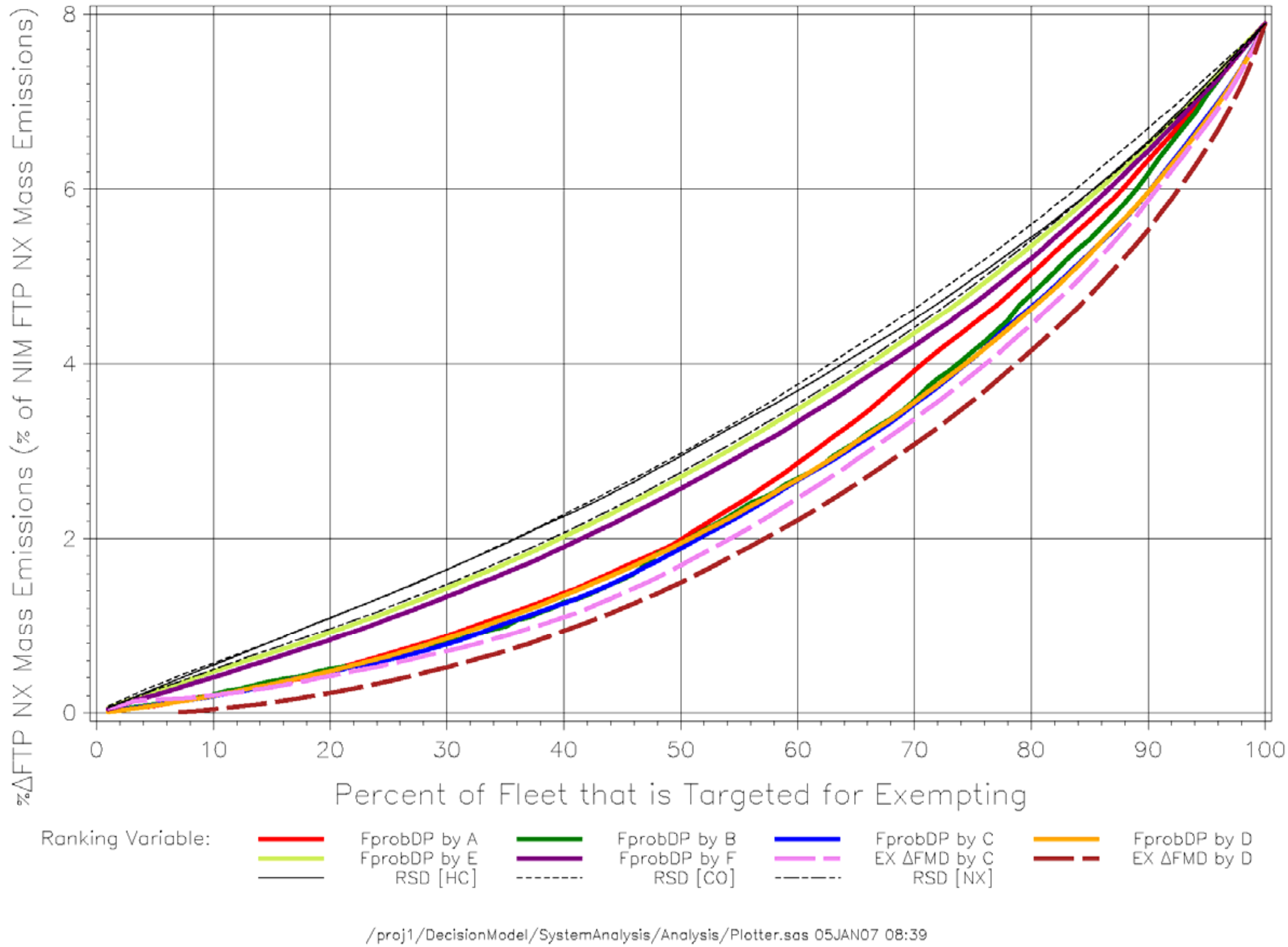


Figure O-13. Pass Fraction of Targeted Vehicles at the Decision Point vs. Percent Fleet Targeting for Exempting (Truth ≈ Model C)

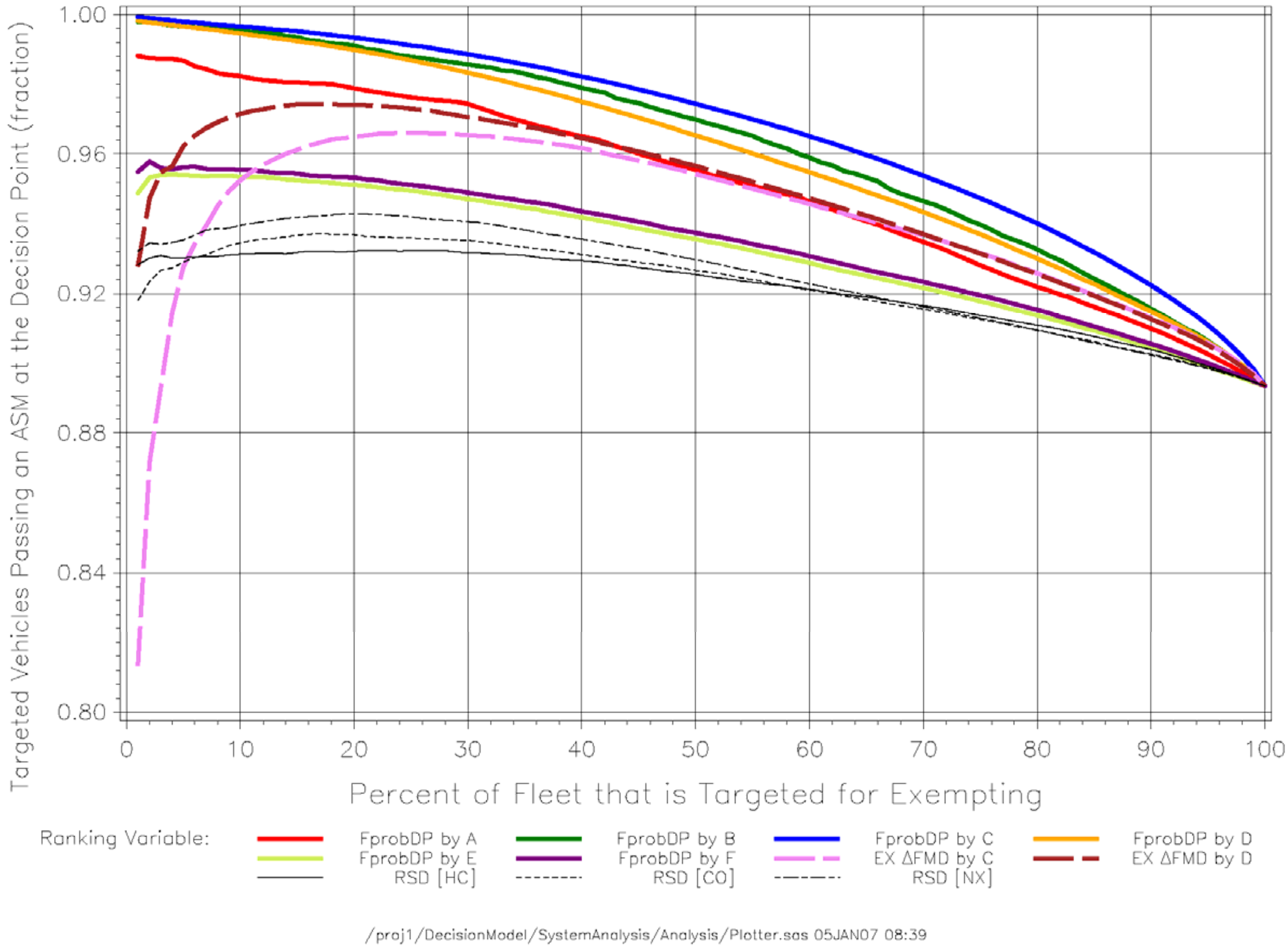


Figure O-14. Change in Failed Miles Driven Over 24 Months vs. Percent Fleet Targeting for Calling-In No-Sticker (Truth ≈ Model C)

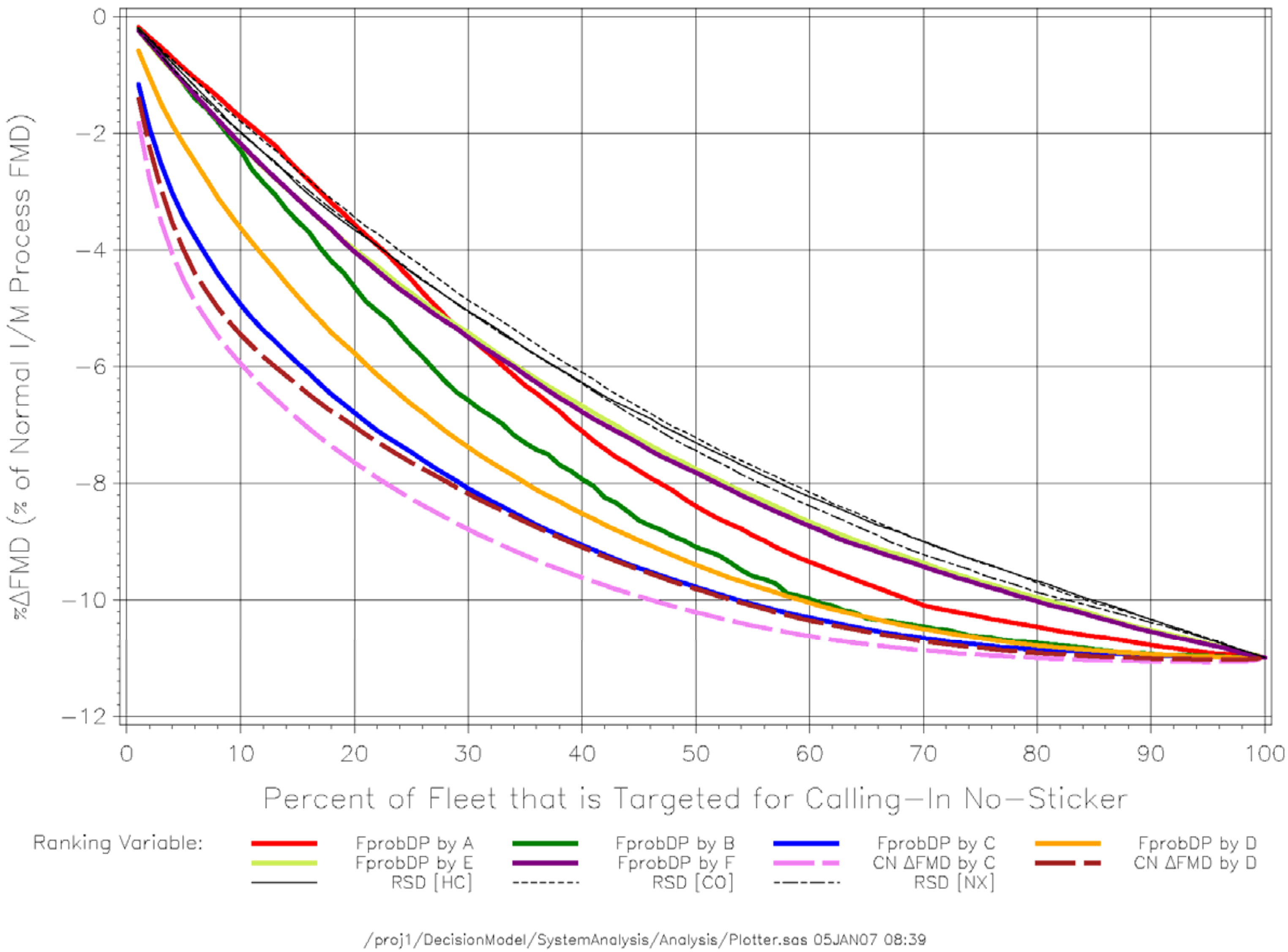


Figure O-15. Change in FTP HC Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Calling-In No-Sticker (Truth ≈ Model C)

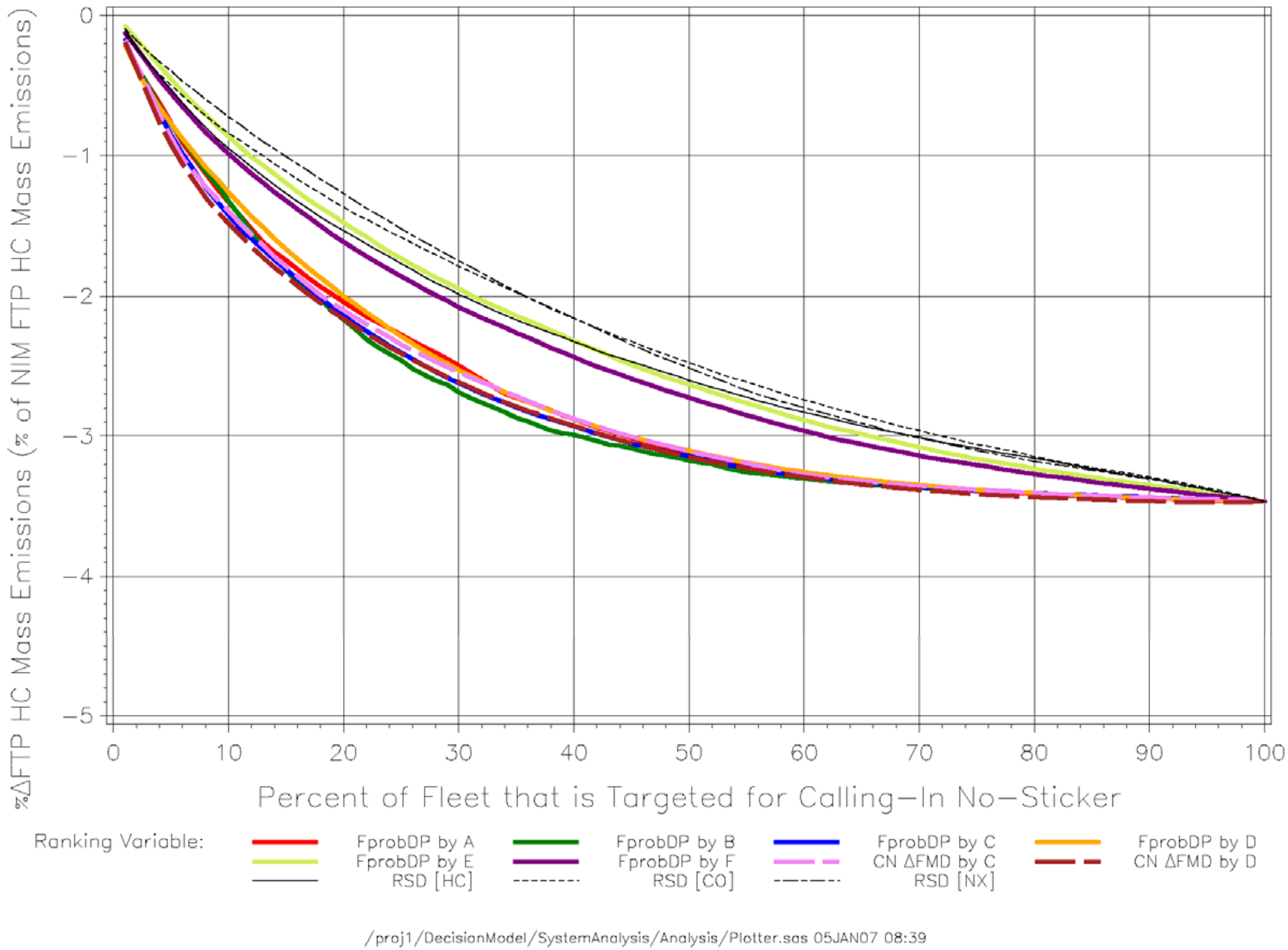


Figure O-16. Change in FTP CO Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Calling-In No-Sticker (Truth ≈ Model C)

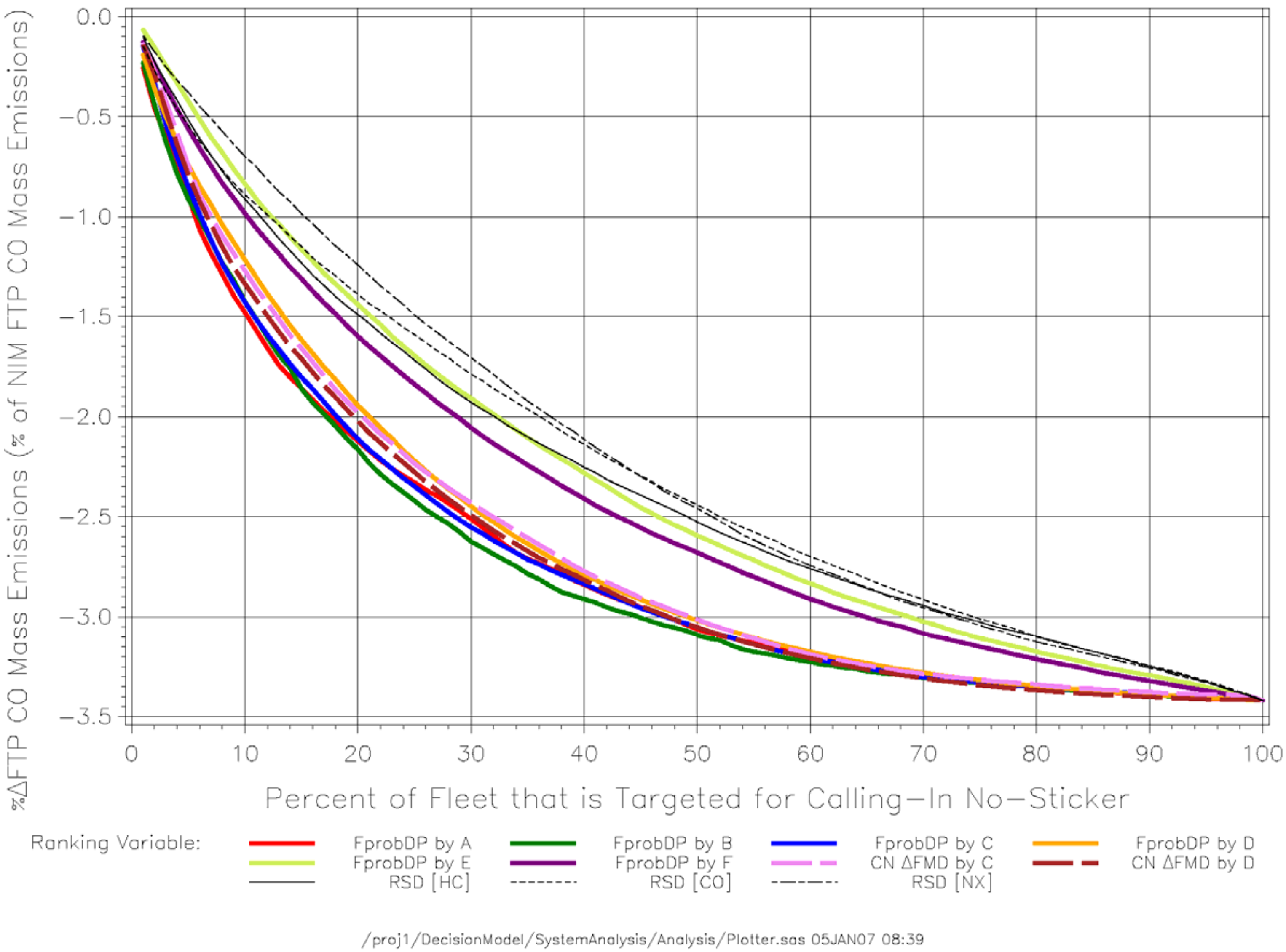


Figure O-17. Change in FTP NX Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Calling-In No-Sticker (Truth ≈ Model C)

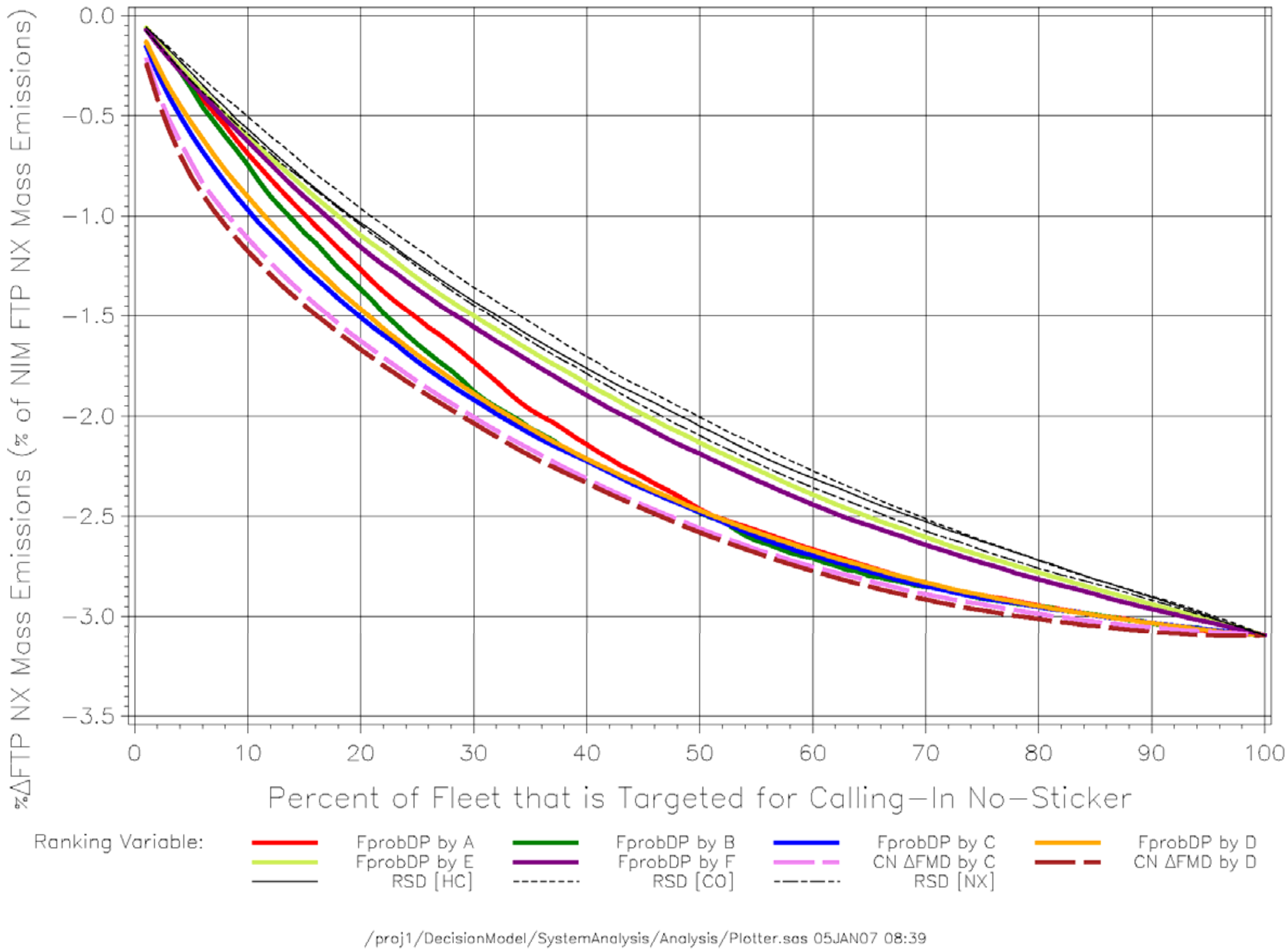


Figure O-18. Fail Fraction of Targeted Vehicles at the Decision Point vs. Percent Fleet Targeting for Calling-In No-Sticker (Truth ≈ Model C)

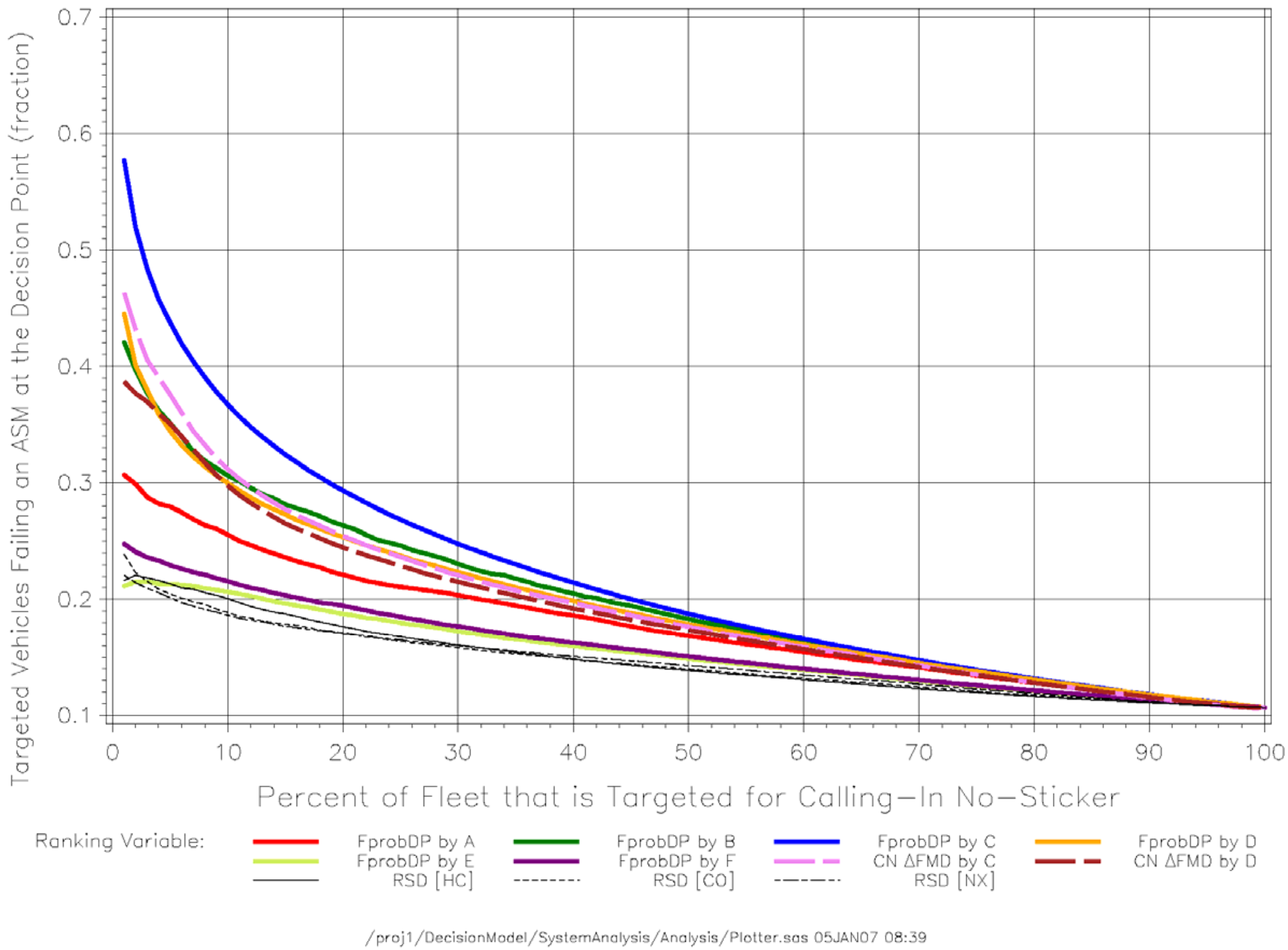


Figure O-19. Change in Failed Miles Driven Over 24 Months vs. Percent Fleet Targeting for Calling-In Sticker (Truth ≈ Model C)

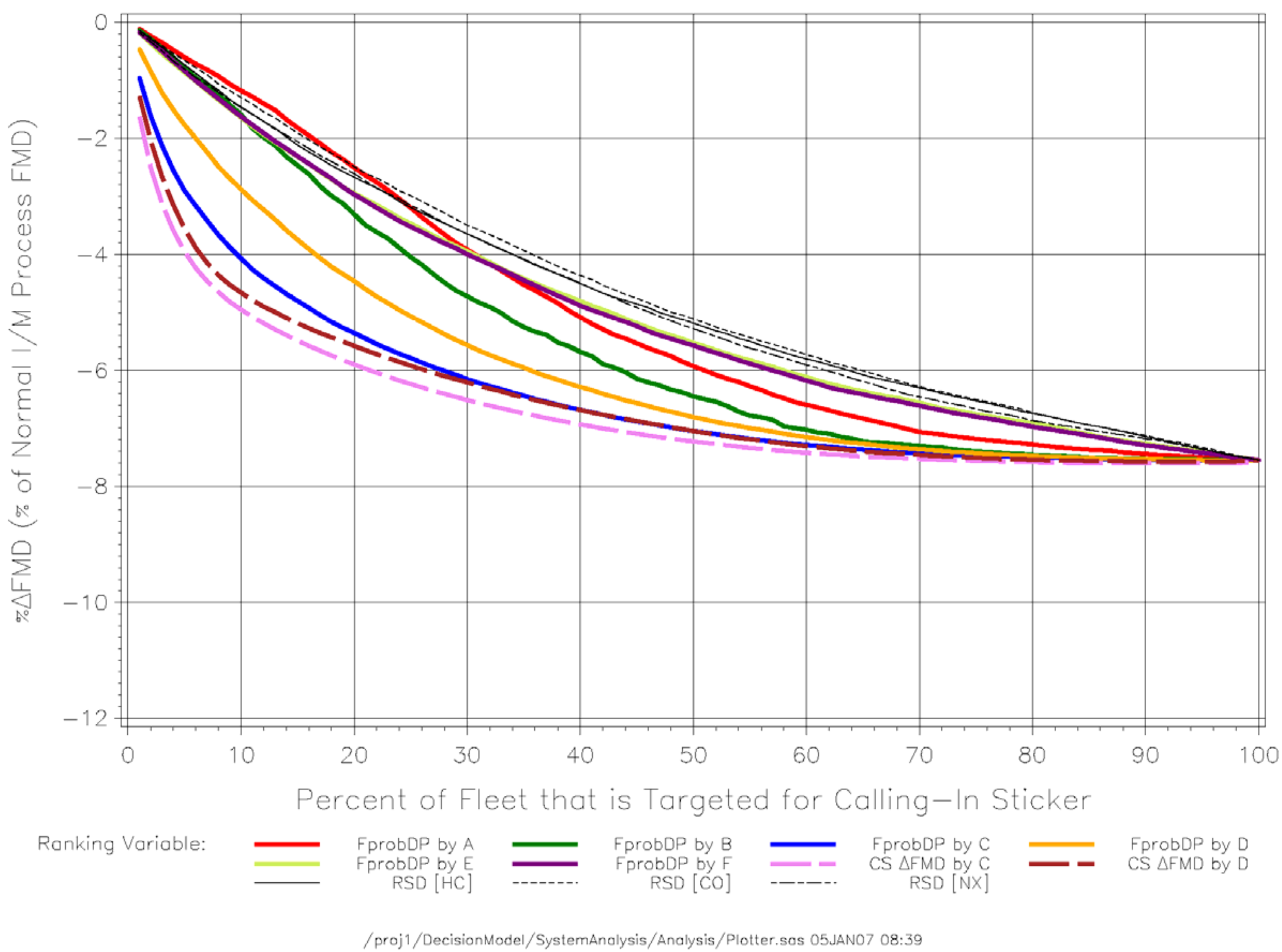


Figure O-20. Change in FTP HC Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Calling-In Sticker (Truth ≈ Model C)

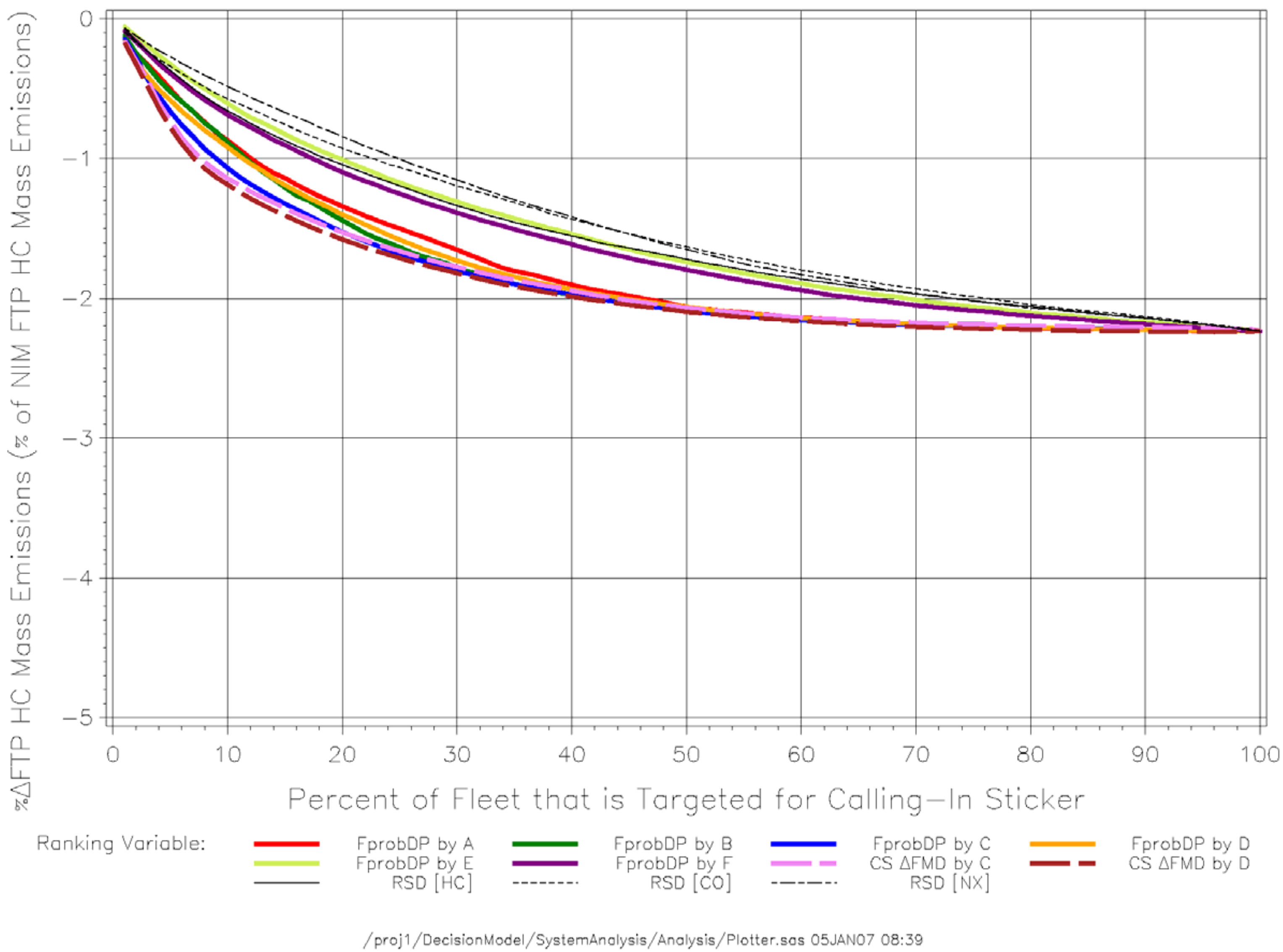


Figure O-21. Change in FTP CO Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Calling-In Sticker (Truth ≈ Model C)

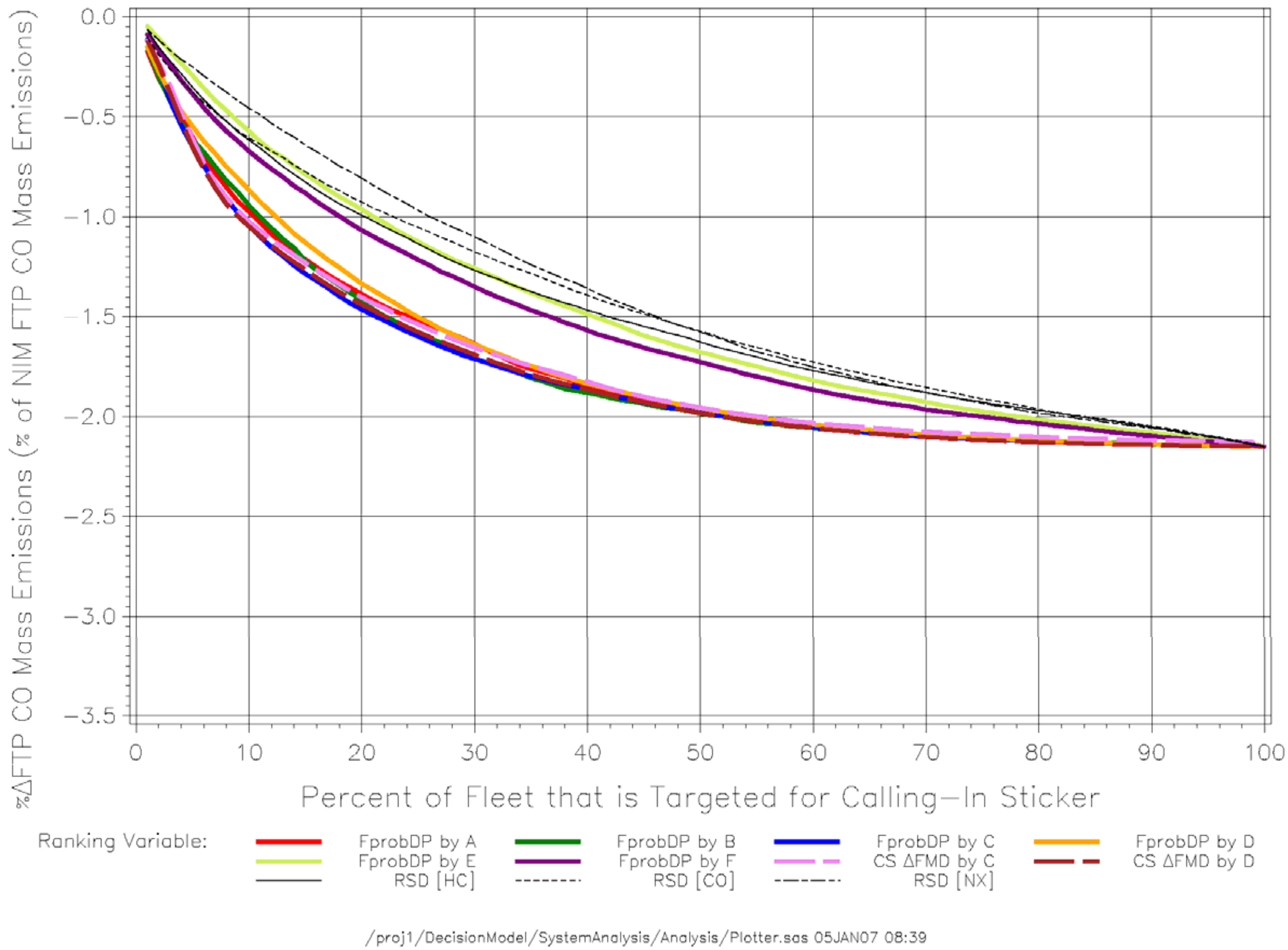


Figure O-22. Change in FTP NX Mass Emissions Over 24 Months vs. Percent Fleet Targeting for Calling-In Sticker (Truth ≈ Model C)

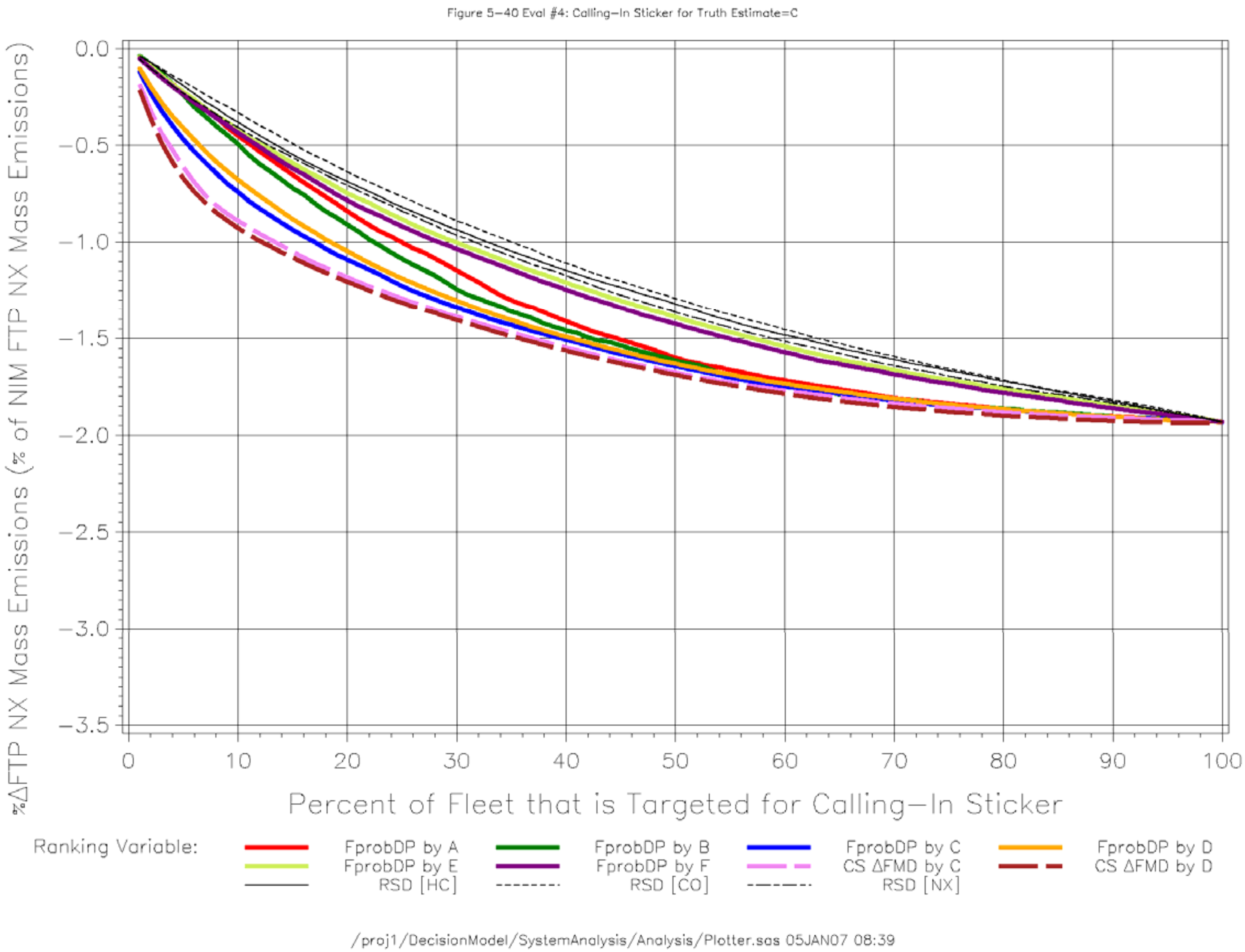


Figure O-23. Fail Fraction of Targeted Vehicles at the Decision Point vs. Percent Fleet Targeting for Calling-In Sticker (Truth ≈ Model C)